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Price behaviour of chickpea in Maharashtra: An economic analysis

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Abstract
This study analyzes market co-integration and predicts short-term prices of chickpeas in selected markets of Maharashtra. The research was conducted in five major chickpea markets of Maharashtra *viz*. Latur, Yavatmal, Nanded, Dharashiv and Buldhana. Monthly time series data of arrivals and prices of chickpeas were collected from these markets, specifically from AGMARKNET and office records of the respective Agricultural Produce Market Committees, covering the period from January 2011 to December 2023.
Econometric tools such as Augmented Dickey-Fuller (ADF) test, Johansen's multiple co-integration test and the Seasonal Autoregressive Integrated Moving Average (SARIMA) model were used for analysis. All price series from the selected markets were non stationary at level and they became stationary after first differencing. The selected markets showed long run equilibrium relationship and co-integration between them with three co-integrating equation. The forecast for chickpea prices was focused on the Latur market, which has the highest arrivals. The data collected from the APMC office of Latur was used to predict the prices for the upcoming twelve months.

Keywords: Market integration, short-term prices, SARIMA model, chickpea prices, ADF Test, forecasting, time series analysis, seasonal differences, APMCs, chickpea markets, Maharashtra

Introduction

India is the major producer and consumer of pulses globally. Chickpea (*Cicer arietinum* L.) is a self-pollinated true diploid (2n=2x=16) cool season leguminous crop. It is also known with different common names *viz*., Bengal gram, gram, garbenzo bean and Chana. Chickpea is a legume which is being cultivated for its edible seed and sprouts across Asia. Chickpea is an important food legume commodity and have a diverse use with specific consumer preference in the global market.

In agriculture, pricing is the single most important indicator of profit or loss. Crops are sown in one growing season and harvested the next, making time a significant problem in agriculture. As a result, price is critical during the marketing process. The study of market integration among different major chickpea markets of Maharashtra help to know the best market for chickpea in Maharashtra. It is useful to the farmers in farming business and farm planning. Thus, the findings of the study would throw light on various issues related to production and marketing of chickpea which would help policy makers, administration and farmers in formulating the appropriate strategies.

The seasonal variations in the market prices influence the farmers income as there are fluctuations in the prices of chickpea year around. In peak arrival of months prices may decline and in lean period they may rise. The markets of chickpea in Maharashtra need to be co-integrated so that same prices of chickpea are realized to the farmers. For better marketing of any agricultural commodity the information about seasonality, seasonal variations, price volatility, price movement across the state and country, etc. is necessary. Analyzing the past trend in the price of commodities is useful in understanding the present scenario and to formulate proper strategies to improve the marketing system. The results of the study are serve as a guide to the Government to formulate marketing policy.

- To study co-integration among major chickpea markets in Maharashtra.
- To predict short-term prices of chickpea in selected markets of Maharashtra.

Materials and Methods Selection of Markets

The study has been confined to the five major markets of Maharashtra state. The data from five major markets namely Latur, Yavatmal, Nanded, Dharashiv and Buldhana were taken on the basis of area of chickpea as these districts ranks highest in area under cultivation of chickpea in Maharashtra. There are 306 APMC markets in Maharashtra but these five were chosen with the assumption that the main APMC of district would be located within that district.

Period of the Study

For the present study monthly time series data on the prices and arrivals of chickpea were collected for the period from January 2011 to December 2023.

Source of Data

The study was based on secondary data. Hence, a reliable source of data is very important to get the real picture. Secondary data consisting of monthly prices and arrivals of chickpea crop was collected from Agriculture Produce Market Committee (APMC). The data available on AGMARKNET was also utilized for analysis purposes.

Analytical tools

Testing of stationarity in price series

To prevent the problem of this spurious regression arising due to non-stationarity, we check the stationarity of time series using the following Augmented Dickey-Fuller (ADF) test. For analysing a long-term equilibrium relationship between various price series, we test the series for co-integration but before that, we need to make sure that the underlying time-series we are working upon must be stationary. Therefore, it is the first step in the analysis of time series. Augmented-Dickey Fuller (ADF unit root test (Dickey and Fuller, 1979) [4] was used in this research study to test the stationarity of time series. The presence of unit root at the level means that the underlying time series is not stationary. So, if the time series is not stationary at level then a time series at first differences is generated which is then further analyzed for stationarity. The ADF test is estimated using the following regression equation:

$$\Delta P = \alpha_0 + \delta_1 t + \beta_1 P_{t-1} + \sum_{j=0}^{q} \beta_1 \Delta P_{t-j} + \varepsilon_t$$

Where, $\Delta Pt = Pt - Pt-1$, $\Delta Pt-1 = Pt-1 - Pt-2$ ………….. $\Delta Pn-1= Pn-1 - Pn-2$ P = Prices in each market

α_0 = Constant term or drift q = The value of lags

εt = White noise error term

The values for this test statistic are compared with the dickey fuller values.

The null and alternate hypotheses tested in ADF are (Ho): $\beta 1$ (Coefficient of Pt-1) is zero.

(H1): $\beta 1 < 0$.

Null hypothesis here states that there was a presence of unit root in the times series and there was non-stationarity whereas alternate hypothesis states that there is no unit root in the series and the series were stationary.

Market Co-Integration: The maximum likelihood (ML) method of co-integration is applied to check long-run wholesale price relations between the selected markets. (Johansen, 1988; Johansen and Juselius, 1990) [7, 6]. The starting point of the ML method is vector auto-regressive model of order k and may be written as

$$P_t = \sum_{i=1}^{k} A_i P_{t-1} + \mu + \beta_r + \varepsilon_t$$

Where,

Pt denotes the (n× 1) vector of non-stationary or integrated of order one, i.e., I (1) prices series. The procedure for estimating the cointegration vectors is based on the error correction model (ECM) representation given by

$$\Delta P_t = \mu + IIP_{t-1} + \sum_{i=1}^{k-1} I_i \Delta P_{t-1} + \beta \mu_t + \varepsilon_t$$

Where, Γi and Πi = n× n matrixes of the coefficient conveying the short and long run information respectively,

μ = Constant term,

t = Trend component

ε_t = n-dimensional vector of the residuals that is identically and independently distributed

The vector ΔPt is stationary which means that Pt is integrated at order one I(1) which will make unbalance relation as long as Π matrix has a full rank of k. In this respect, the equation can be solved by inversing the matrix Π -1 for Pt and as a linear combination of stationary variable (Kirchgasser *et al.*, 2012) [8]. The stationary linear combination of the Pt is determined by the rank of Π matrix. If the rank r of the matrix Π r=0 the matrix is the null and the series underlying is stationary. If the rank (r) of the matrix Π is such that 0 < rank of (Π) = r < n then there are n × r cointegrating vectors. The central point of the Johansen's procedure is simply to decompose Π into two n × r matrices such that Π=αβ'. The decomposition of Π implies that the β'Pt are r stationary linear combination. Johansen and Juselius, (1990) [6] proposed two test statistics (Trace statistic and Max Eigen test statistics) to determine the number of co-integrating vectors which are given by

$$I_{trace} = -T \sum_{i=r_{+1}}^{N} \ln(1-\lambda)$$

$$\lambda_{max} = -T \ln(1 - \hat{\lambda}_{r_{+1}})$$

Where, r = The number co-integrated vector,

$\hat{\lambda}_r$= The eigenvalue

$\hat{\lambda}_{r_{+1}}$ = The (r + 1)th largest squared eigenvalue obtained from the matrix Π T = Effective number of observations.

The trace statistics tested the null hypothesis of 'r' co-integrating vector(s) against the alternative hypothesis of r co-integrating relations. The Max Eigen statistic tested the null hypothesis (r =0) against the alternative (r + 1).

Prediction of Prices

Univariate Seasonal ARIMA will be used to forecast the prices in short run. The data on prices refers to modal prices in a month. Modal price was considered superior to the monthly average price as it represented the major proportion of the commodity marketed during the month in a particular market.

A mixed Auto Regressive Integrated Moving Average (ARIMA) model developed by Box and Jenkins (1976) was employed for analysis of the data, which involved selection of appropriate model, estimation of parameters, diagnostic checking and finally forecasting the prices. The ARIMA (p, d, q) model can be represented by the general forecasting equation known as Box-Jenkins equation. The Seasonal ARIMA model (SARIMA) is formed by adding seasonal terms in the ARIMA models:

SARIMA (p, d, q) (P, D, Q) [S],

Where,

p is a non-seasonal autoregressive order, P is a seasonal autoregressive order,

q is a non-seasonal moving average order, Q is a seasonal autoregressive order,

d and D are the order of common difference and seasonal difference

ARIMA model

ARIMA models are often referred to as Box-Jenkins models. In this study, the analysis performed by ARIMA is divided into four stages. (i) Identification of the model, (ii) Estimation of parameters of the model, (iii) Diagnostic Checking of the model, and (iv) Forecasting. The details of the estimation and forecasting process are discussed below.

Step 1: Identification of the model

The first step of applying the Box-Jenkins forecasting model is to identify the appropriate order of SARIMA (p, d, q)(P, D, Q)s model. Identification for the orders of seasonal and nonseasonal parameters, p, q, and P, Q. That could be obtained by looking for significant autocorrelation and partial autocorrelation coefficients (Yet another application of the autocorrelation function is to determine whether the data contains a strong seasonal component). This phenomenon is established if the autocorrelation coefficients at lags between t and t-12 are significant). The order of d and D are estimated through I(1) or I(s) process of unit root stationary tests. The model specification and selection of order p, P and q, Q involved plotting of autocorrelations functions (ACF) and partial autocorrelations functions (PACF) or correlogram of the series at different lag length. If the PACF displays a sharp cutoff while the ACF decays more slowly (i.e., has significant spikes at higher lags), we say that the series displays an AR signature. However, if the ACF displays a sharp cutoff while the PACF decay more slowly, we say that the series displays an MA signature. The autocorrelation functions specify the order of moving average process, and partial autocorrelations function to select the order of the autoregressive process.

Step 2: Estimation of the model

ARIMA models are fitted and accuracy of the model was tested on the basis of diagnostics statistics. At the identification stage one or more Seasonal ARIMA models are tentatively chosen that seem to provide statistically adequate representations of the available data. The next step is to specify an appropriate regression model and estimate it. Seasonal ARIMA models are fitted and accuracy of the model was tested based on diagnostics statistics. Then we attempted to obtain precise estimates of parameters of the model by nonlinear least square method.

Step 3: Diagnostic checking

After having estimated the parameters of a tentatively identified seasonal ARIMA model, it is necessary to do diagnostic checking to verify that the model is adequate. Examining the Autocorrelation Function (ACF) and Partial ACF (PACF) of residuals may show up an adequacy or inadequacy of the model. If it shows random residuals, then it indicates that the tentatively identified model is adequate.

The best model was selected based on the following diagnostics:

Low Akaike Information Criteria (AIC)

AIC was estimated by AIC = −2 loge (L) + 2 m, where, m = p+q +P+Q and L is the likelihood function.

Low Bayesian Information Criteria (BIC)

The Bayesian Information criterion is a criterion for model selection among a finite set of models. It is based, in part, on the likelihood function, and it is closely related to Akaike information criterion (AIC).

Sometimes, Bayesian Information Criteria (BIC) was also used and estimated by

$$BIC = -2\log_e(L) + \log_e(N)m.$$

Where,

N is number of observation and m is the number of parameters.

Low Hannan-Quinn Criterion (HQC)

Hannan-Quinn Criterion is a criterion for model selection among a finite set of model. It is not based on the log-likelihood function (LLF), but is related to Akaike's information criterion.

The minimum Root Mean Square Error (RMSE) and Mean Absolute Percent Error (MAPE) was used as a measure of accuracy of the models.

Box Q (LBQ) statistic

This was also judged by Ljung-Box Q (LBQ) under null hypothesis that autocorrelation co-efficient up to lag k is equal to zero. LBQ is used to assess assumptions after fitting a time series model (SARIMA), to ensure that the residuals are independent.

Step 4: Forecasting

Once the first three steps of seasonal ARIMA model are over, then we can obtain the forecasted values by estimating the appropriate model, which is free from problems.

Results and Discussion

Augmented Dickey-Fuller (ADF) test

The unit root results using ADF test for three equations i.e. no intercept, intercept and intercept and trend for level and first differenced price series were tested and results were reported in table 1. The Augmented Dickey-Fuller (ADF) test was conducted to evaluate the stationarity of chickpea price series across five markets in Maharashtra *viz*. Latur, Yavatmal, Nanded, Dharashiv and Buldhana. In the at level series, all values for the selected markets exceed the critical values for both the 1% and 5% significance levels, indicating a lack of stationarity. Specifically, Latur, Yavatmal, Nanded, Dharashiv, and Buldhana show values such as -0.39, 0.07, 1.61, 0.21, and 0.83, respectively. However, after first differencing, all values fall below the critical values at both significance levels, confirming stationarity. For instance, the first difference series shows values of -10.35 for Latur, -11.14 for Yavatmal, -10.68 for Nanded, -14.62 for Dharashiv, and -10.31 for Buldhana. These findings confirm that the differencing process effectively stabilized the price series across all markets.

Table 1: Results of ADF test

Markets	Equation I	Equation II	Equation III
At level series			
Latur	-0.39	-2.50	-2.78
Yavatmal	0.07	-2.96	-3.34
Nanded	1.61	-0.34	0.06
Dharashiv	0.21	-3.15	-3.22
Buldhana	0.83	-0.87	-1.86
At 1st difference series			
Latur	-10.35	-10.30	-10.24
Yavatmal	-11.14	-11.11	-11.07
Nanded	-10.68	-10.89	-10.90
Dharashiv	-14.62	-14.61	-14.55
Buldhana	-10.31	-10.40	-10.34
Critical value at 5%	-1.94	-2.88	-3.44
Critical value at 1%	-2.58	-3.48	-4.02

Johansen's co-integration test

The Johansen co-integration test revealed significant long-term equilibrium relationships among chickpea prices in five major markets in Maharashtra. This study examined chickpea prices across five major Agricultural Produce Market Committees (APMCs) in Maharashtra *viz*. Latur, Yavatmal, Nanded, Dharashiv and Buldhana to determine if a stable long-term equilibrium exists among these markets. The results indicate significant co-integration, with the trace statistic of 152.75 exceeding the critical value of 88.80 and the maximum eigenvalue statistic of 62.38 surpassing 38.33 for the hypothesis of no co-integrating equations. Further analysis revealed at least three significant co-integrating relationships, confirming that, despite short-term fluctuations, the markets exhibit cohesive long-term price movements. The test also showed evidence of up to three co-integrating relationships, confirming that the markets are interlinked through multiple long-term price movements. This suggests that despite short-term price fluctuations, there is a stable and cohesive pricing mechanism across the markets.

Table 2: Results of Johansen co-integration test

Equation tested	Hypothesized No of CE (s)	Trace Statistic	Critical value @5% level	Max-Eigen Statistic	Critical value @5% level
Latur, Yavatmal, Nanded, Dharashiv, Buldhana	None *	152.75	88.80	62.38	38.33
	At most 1*	90.36	63.88	39.01	32.12
	At most 2*	51.36	42.92	30.32	25.82
	At most 3	21.03	25.87	15.34	19.39
	At most 4	5.69	12.52	5.69	12.52

Note: Trace test indicates 3 co-integrating equations significant at the 5 percent level of significance (* indicates co-integrating equations)

Estimates of best fitted SARIMA model (2, 1, 2) (0, 1, 0)

Table 3 details the estimates for the SARIMA model (2, 1, 2)(0, 1, 0) applied to chickpea price data. The significant autoregressive parameters indicate that past prices notably influence current prices, with Lag 1 at 0.48 and Lag 2 at -0.97. The moving average parameters also show significance, with Lag 1 at 0.42 and Lag 2 at -0.92, indicating that past forecast errors affect current prices. The model incorporates first-order and seasonal differences to account for trends and seasonal variations. Overall, the SARIMA model effectively captures the dynamic patterns of chickpea prices, demonstrating robustness and suitability for forecasting.

Table 3: Estimates of best fitted SARIMA model (2, 1, 2) (0, 1, 0) for chickpea price series

Parameter	Estimate	SE	't' value	Significance
AR	Lag 1	0.48	0.03	< 0.001
	Lag 2	-0.97	0.03	< 0.001
Difference		1		
MA	Lag 1	0.42	0.06	< 0.001
	Lag 2	-0.92	0.06	< 0.001
Seasonal Difference		1		

Short run Price Forecasting of Chickpea Crop

The monthly modal price data of chickpeas was collected over 13 years (From January 2011 to December 2023) for major chickpea markets in Maharashtra, including Latur, Yavatmal, Nanded, Dharashiv and Buldhana. For forecasting chickpea prices, it was confirmed that all five markets are co-integrated. Consequently, the forecast for chickpea prices was focused on the Latur market, which has the highest arrivals. The data collected from the APMC office of Latur was used to predict the prices for the Latur market for the upcoming twelve months.

The study aimed to predict short-term chickpea prices in Latur, Maharashtra, using a Seasonal ARIMA (SARIMA) model. We have transformed original chickpea price series to logarithmic series and first difference series to achieve stationarity and to control the heteroscedasticity. The SARIMA model (2, 1, 2) (0, 1, 0) was identified as the best-fitting model for forecasting, accounting for both trend and seasonality. For the estimation of models for the Latur APMC chickpea market, SPSS packages were utilized to evaluate and estimate the top 20 SARIMA models. Among these, the best-fitting model was selected based on the lowest Akaike Information Criterion (AIC) value. The model with the least AIC, which was (2, 1, 2) (0, 1, 0), proved to be the most effective for forecasting prices. Consequently, this model was chosen for predicting future chickpea prices, as it provided the best balance between model fit and complexity. The forecasts for 2024 showed a clear pattern of price fluctuations consistent with historical trends, indicating the model's robustness in capturing the dynamics of chickpea prices.

Table 4: Forecast values of chickpea prices in Latur market in Maharashtra

Sr. No.	Month	Forecast	UCL	LCL
1	Jan- 2024	5891	7435	4599
2	Feb-2024	6002	8382	4165
3	Mar-2024	6367	9547	4051
4	Apr-2024	5879	9280	3505
5	May-2024	6160	10168	3465
6	Jun-2024	6473	11180	3427
7	Jul-2024	6277	11330	3129
8	Aug-2024	6896	12914	3263
9	Sep-2024	7634	14738	3457
10	Oct-2024	7834	15579	3397
11	Nov-2024	8044	16509	3327
12	Dec-2024	7412	15684	2925

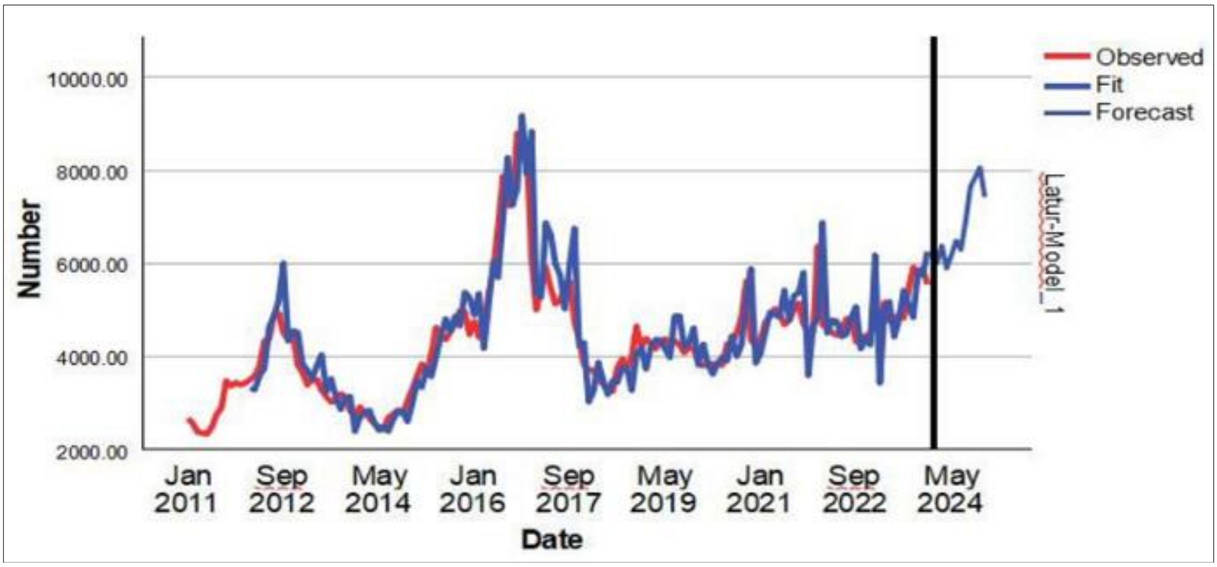

Fig 1: Observed, fitted and forecasted monthly prices of chickpea in Latur, APMC using SARIMA model (2, 1, 2) (0, 1, 0)

Conclusion

The stationarity analysis of chickpea price series across Maharashtra markets revealed that all markets exhibited non-stationarity at the level series but achieved stationarity after first differencing. The Augmented Dickey-Fuller (ADF) test results indicated that Latur, Yavatmal, Nanded, Dharashiv, and Buldhana all required differencing to become stationary, confirming they were integrated of the same order (I(1)). The Johansen co-integration test confirmed that chickpea prices across the major markets in Maharashtra were integrated with up to three significant long-term equilibrium relationships. This indicated that, despite short- term fluctuations, there was a stable and interconnected pricing mechanism among these markets. The strong evidence of co-integration supported the view that the markets were well-integrated, with price movements in one market systematically influencing movements in others over the long term. The forecasting analysis for chickpea prices in the Latur market, extending through December 2024, indicated a general upward trend. The SARIMA model (2, 1, 2) (0, 1, 0) effectively forecasted short-term prices, demonstrating strong predictive capability by accounting for both seasonal and trend components. Forecasted prices were expected to start at Rs. 5,891 in January 2024 and increase to Rs. 8,044 by November 2024, before decreasing in December. The associated upper control limits (UCL) and lower control limits (LCL) reflected the range of uncertainty around these forecasts, showing broader variability during peak months like October and November 2024. These insights provided a clear understanding of anticipated price trends and fluctuations in the market, guiding stakeholders in their decision-making processes.

Policy implication: The forecast predicts lower prices immediately after harvest (January to March), farmers should consider investing in storage facilities to hold their produce until prices are projected to rise later in the year.

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