FORECASTING ARECA NUT MARKET PRICES USING THE ARIMA MODEL: A CASE STUDY OF INDIA

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Abstract
India is the major producer of Areca nut in the world. Volatile demand and price are the major challenges for the Areca nut growers in India. The use of time series models to manage the price risk has become the interest of academicians today. This paper deals with developing an appropriate model to predict the prices of a new variety of Areca nut in Karnataka using monthly price data for the period January 2009 to December 2018. Box Jenkins ARIMA methodology is used to develop the model. Along with ARIMA estimates, log-likelihood, Akaike's information criterion (AIC) and Bayesian (BIC) information criterion statistics are also estimated to decide on the appropriate model. ACF and PACF correlograms for residuals of ARIMA are used to do the diagnostic check of the selected ARIMA model. Appropriate model to forecast the new variety Areca nut price is ARIMA (3, 1, 3).

Keywords: *investment behavior, Areca Nut, price forecasting, ARIMA models, volatility, time series, ACF, PACF, stock market forecasting*

Classification JEL: *C22, G11, G17*

1. Introduction

India is the largest producer and consumer of Areca nut in the world, and it contributes more than 50% for world production (Hegde & Deal, 2014). The next large producers of Areca are Bangladesh and Srilanka, their contribution to the world total production is 14% and 10% respectively. Post partition of the country, India had to import Areca from other countries because 50% of the production area was with Bangladesh, which resulted in an increased price for areca nut in the country and further policies of the Indian Government were to reduce the imports. Ullal et al. (2021) highlighted some very interesting aspects such as the fact that Indian consumers living in the north of the country perceive themselves as independent, while Indian consumers living in the South India are much more stable and integrated as essential part of their families and social groups. In addition, Nethravathi et al. (2020) revealed that potential changes in the dynamics of consumer behavior exhibit significant influences on all business enterprises over a period of time.

Hence in 1970s import of Areca was equal to zero. This was the time many farmers in South India started planting Areca because of the attractive price (Viswanath & Narappanavar, 1980). More than 65% of the total areca produce in India is grown in Karnataka. Coastal districts of the state are significant contributors because of heavy rainfall in these districts (Chowdappa & Cheriyan, 2017). Excess rainfall, labour unavailability, and instability in demand and price for Areca nut are the significant challenges for producers and traders of this commodity (Ramappa, 2013). Spulbar et al. (2020) argued that global financial liberalization causes a much weaker impact on developing economies like India, by comparative analysis with developed economies.

Sri Lanka and Indonesia are the two largest exporters of Areca nut to India, nearly 18000 tons of areca we have imported from these two countries in the recent year 2017 -2018. Maldives, UAE, and the USA are the three major importers of Areca from India (Chowdappa & Cheriyan, 2017). Trade volume in the international and domestic markets and the exchange rate of trading countries have made the Areca nut market more volatile in recent years (Ramappa, 2013). Traders, growers and industrial users of Areca nut are facing problems because of this volatile market and these stakeholders of Areca nut industry are sufferers of this price risk. On the other hand, Pinto et al. (2020) argued that the traditional approach of theory supports the hypothesis of the existence of a direct linear linkage between the risk and stock returns. Proper forecasting model will help the farmers and traders of Meghalaya and Assam to generate profitable income, ARIMA approach is the widely used approach in univariate time series forecasting(Shil et al., 2013). Predictions using historical data were widely used in econometric studies. Still, the accuracy of such predictions was very poor, and this drawback is the motivation for the success of AR, MA, ARMA and ARIMA models in time series analysis (Cortez et al., 2018). Moreover, Meher et al. (2021) suggested that ARIMA (Auto-Regressive Integrated Moving Average) is very useful in stock market forecasting as a benchmark model.

2. Literature review

Various statistical models are developed and used for predictions in time series data. Various researchers (Abdullah, 2012; Abonazel and Abd-elftah, 2019; Adebiyi et al., 2014; Alsharif et al., 2019; Chin and Fan, 2005; Darekar and Reddy, 2017; Farooqi, 2014; Jakaša et al., 2011; Mondal et al., 2014; Nochai and TItida, 2006; Ohyver and Pudjihastuti, 2018; Shathir and Saleh, 2016; A. Shathir et al., 2019; Sukiyono et al., 2018; Tse, 1997) have developed and used ARIMA model to forecast different agricultural commodity prices, stock prices, oil prices, GDP, gold bullion, export-import values, electricity price, and real estate prices. Mishraet al., (2019) have used a multiple regression model to forecast the price of potato in Uttar Pradesh. Bowman and Husain (2004) have used futures prices to predict the prices of 15 agricultural commodities and concluded that various time series models or statistical techniques could be used to generate models based predictions. Xiong et al. (2018) have used STL and extreme learning machines (ELM) methods to forecast agricultural commodity prices in China.

To develop the ARIMA model for the prediction of time-series data, the data used for the model should be stationary. There are various statistical tests available to check the stationarity of the series. Auto Correlation Function (ACF), Partial Auto Correlation Function (PACF), and Line Plots are the famous graphical analysis used in many types of research. (Abonazel and Abd-elftah, 2019; Case et al., 2019; Sukiyono et al., 2018; Farooqi, 2014; Adebiyi and Ayo, 2014; Shil et al., 2013; Abdullah, 2012; Jakaša et al.,2011; Nochai and TItida, 2006) have used ACF and PACF correlogram to check the stationarity of time series and if the series is nonstationary, then first-order differencing was made for the series to make it stationary.

Sukiyono et al., 2018; Darekar and Reddy, 2017; Goswami, 2014; Nochai and TItida, 2006 and Ohyver and Pudjihastuti, 2018 have used ACF and PACF correlograms to identify the parameters p, d, q of the ARIMA model.K.Das, 1990; Yadava, 1977; Viswanath, 1980; Varmudy, 2000; Devi, 2000; Bhagat and Dhar, 2013; Ramappa, 2013; Vignesh, 2013; Hegde et al., 2014; Manojkumar and Scenario, 2014; Staples and Bevacqua, 2016; Chowdappa et al., 2017; Gupta et al., 2018 have discussed the economics of areca nut in India. Areca nut was traditionally used for Gutka, but now there are many alternative industrial uses such as medicine, wine, and paint manufacturing. Demand for Areca nut is increasing in the foreign markets as well.

3. Data collection and research methodology

The data for this study is collected from the official website of open government data (OGD) platform India. The monthly price data for a new variety of Areca nut were downloaded from January – 2009 to December 2018. There are 5 varieties of Areca nuts trading in the market; new variety is the famous among those 5 verities because of the inadequate warehouse facility among majority farmers. Hence, we have taken the price series of new variety areca nut to develop the ARIMA model.

In the initial forecasting studies, linear regression models were used. The simple bivariate linear model gives the following equation.

$$\varepsilon(Y_t) = \alpha + \beta(X_t) \ldots (1)$$

In equation 1, α is the intercept, the value of dependent variable $\varepsilon(Y_t)$, when the value of independent variable X= 0, and $\beta$is the slope of the regression line, the rate of change in the dependent variable for one unit change in the independent variable. The deviation of the observation can be added adjusted by adding error term ε_k to the equation (Rawlings et al., 1998). If the value of the dependent variable is influenced by more than one independent variable, then commonly used methodology was multiple linear regression models in financial literature (Chris Brooks, 2008).

$$y_t = \alpha + \beta_1 x_{1t} + \beta_2 x_{2t} + \cdots + \beta_k x_{kt} + \varepsilon_t \ldots (2)$$

In the 2nd equation: $\alpha, \beta_1, \beta_2 \text{and} \beta_k$ are the constants for multiple independent variables, the rate of change in the dependent variable for one unit change in independent variable$x_1, x_2 \text{and} x_3$. However, both models cannot be applied unless we have a strong known independent which influences the value of our variable in interest. When a structural model is not suitable, when the independent variables are not measurable, observable or when the frequency of an independent variable is not enough, then univariate time series models are advised to use (Chris Brooks, 2008). Box – Jenkins Autoregressive integrated moving average (ARIMA) methodology is widely used today to develop a forecast model and this method follows systematic procedures to develop a forecasting model. The ARIMA is the composite model of three processes; they are autoregressive, integration and moving average. In the autoregressive process, the independent values will be the past values of the dependent variable itself; hence, the general form of the autoregressive model will be as follows.

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \cdots + \alpha_p y_{t-p} + \varepsilon t \ \ldots (3)$$

Equation 3 is the general representation of AR (p) model, where α_0, α_1 and α_p are the constants, y_{t-1} and y_{t-p} are the past values of the dependent variable. In the moving average process, the value of the dependent variable for period *t* is the linear function of current and immediate past shocks or innovations(Kozhan, 2009). Hence, the general form of moving average will be as follows.

$$y_t = \alpha_0 + \varepsilon t + \beta_1 \varepsilon_{t-1} + \cdots + \beta_q \varepsilon_{t-q} \ \ldots (4)$$

In equation 4, α_0, β_1 and β_q are constants, and εt, ε_{t-1} and ε_{t-q} are the past values of error terms. The combined process of AR and MA process is ARMA; following equation 5 is the general representation of ARMA (*p*, *q*) model.

$$y_t = \alpha_1 y_{t-1} + \cdots + \alpha_p y_{t-p} + \varepsilon t + \beta_1 \varepsilon_{t-1} + \cdots + \beta_q \varepsilon_{t-q} \ \ldots (5)$$

To apply any time series methodology, series must be stationary; estimations of nonstationary series will be spurious. For monthly areca nut price series, we have plotted Line plots, autocorrelation function (ACF) and partial autocorrelation function (PACF) correlograms to check the stationarity of the series. As the series follows an upward trend (nonstationary), we have taken the first order differenced series to accomplish all other procedures of the model. Once the series becomes stationary, the methodology follows steps shown in Figure 1.

Figure 1: ARIMA methodology process

Accurate choice of these *p, d, and q* values for the model is the biggest challenge in this model. Gujarati et al., (2009)suggests ACF and PACF correlograms of differenced series to identify the AR and MA process terms. It is also advised to take a few alternative models for estimation process because many researchers believe that along with experience experiment also plays a vital role in developing the ARIMA model. Once the alternative models are developed, we have run all the alternative ARIMA models to estimate significant coefficients, variance (Volatility), log-likelihood, Akaike's information criterion (AIC) and Bayesian (BIC) information criterion statistics. Estimated statistic values are tabulated to decide on the most appropriate model. Finally, we have estimated the residuals of the selected ARIMA model. Further, the ACF and PACF correlograms were plotted to do the diagnostic check of the chosen model.

4. Empirical analysis and discussion

The autoregressive integrated moving average (ARIMA) is the combination of autoregressive (AR) and moving average (MA) process of an integrated or differenced time series model. If the time series used for the model does not have a unit root, that is if the series is stationary, then the ARMA model can be developed as the integration or differencing of the series is not necessary (Gujarati et al., 2009).

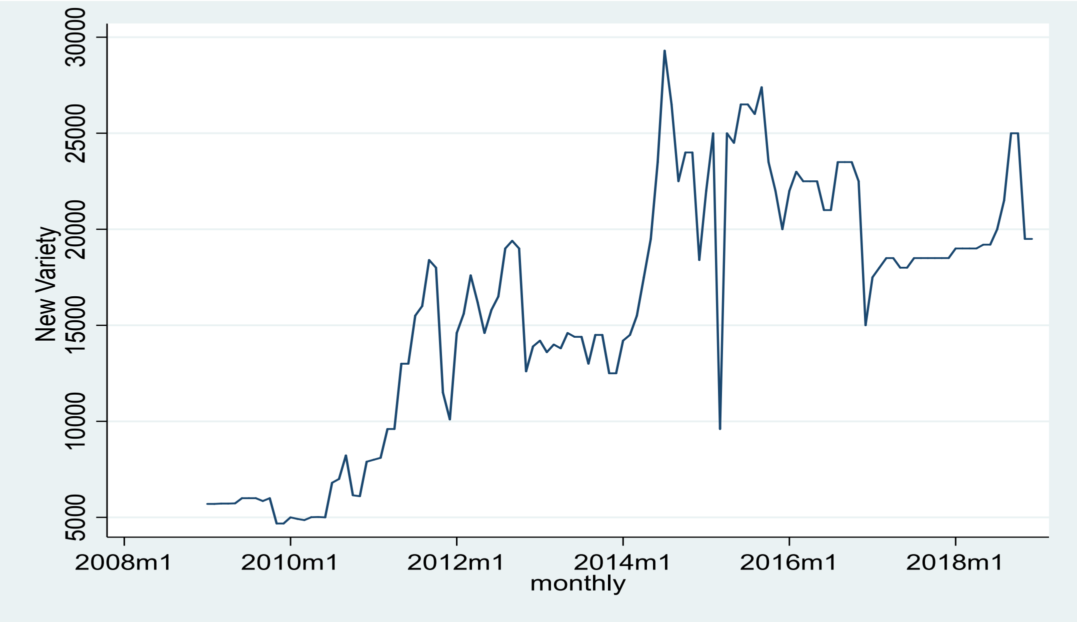

Figure 2: Timeline plot of Areca nut price series
Source: Authors processing using areca nut price series

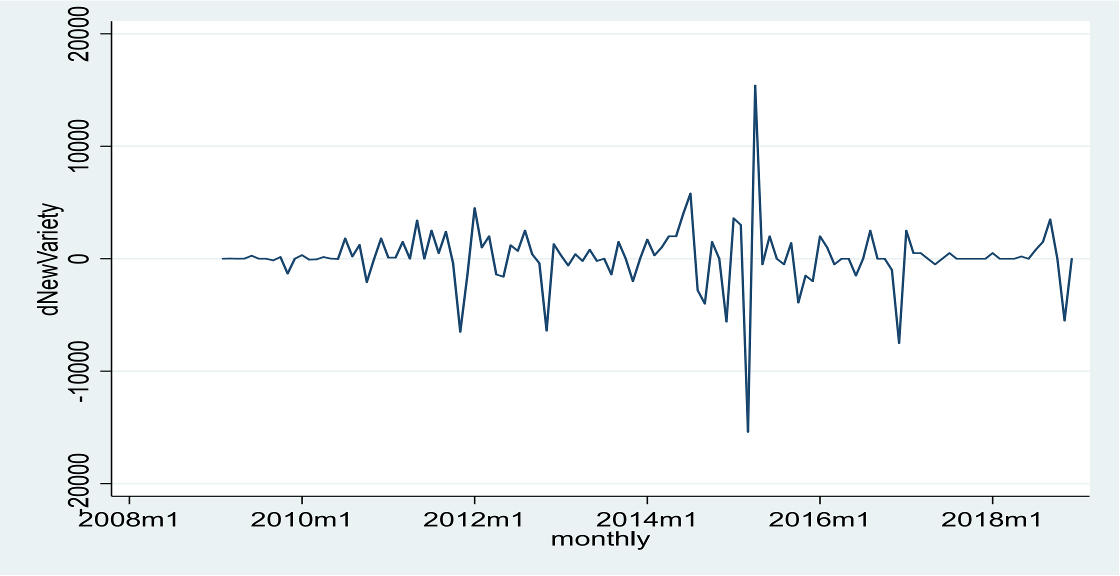

Figure 3: Timeline plot of differenced Areca nut price series
Source: Authors processing using areca nut price series

Gujarati et al., (2009) have advised plotting the time series to get an idea of the stationarity of the time series. Figure 2 shows an upward trend, and the trend is not reverting to zero, which says that the log of Areca nut price is increasing. This suggests that the log of the

Areca price series has got a unit root, or the series is not stationary. Figure 3 is the plot of the first-order differences of the Areca price series. Unlike Figure 2, we cannot see any trend in Figure 3 that is the time plot of differenced price series, and we can also observe that trend is reverting to zero which confirms the constant mean condition. Therefore, now the first differenced Areca price series is stationary. Similarly, correlograms of Auto Correlation Function (ACF) and Partial Autocorrelation Function (PACF) can also be seen to check the stationarity of the time series. Figure 4 shows the correlograms of ACF for Areca price series, up to 10 lags all are outside the 95% confidence bands. There is a gradual decrease in autocorrelation up to 10th lag this confirms the nonstationarity of Areca price series. Figure 5 shows the ACF correlograms of differenced Areca nut price series, which will not show any behaviour of Figure 4 to call that series as stationary. Except for the first lag in Figure 5, all other lags are not statistically different from zero. Therefore, now the first order differenced Areca nut price series is a stationary series.

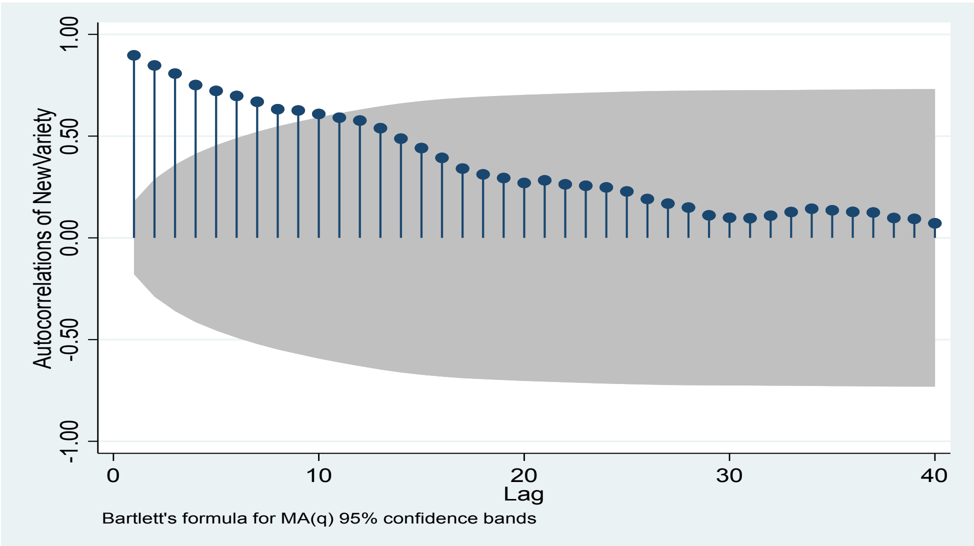

Figure 4: ACF Correlograms of the Areca nut price series
Source: Authors processing using areca nut price series

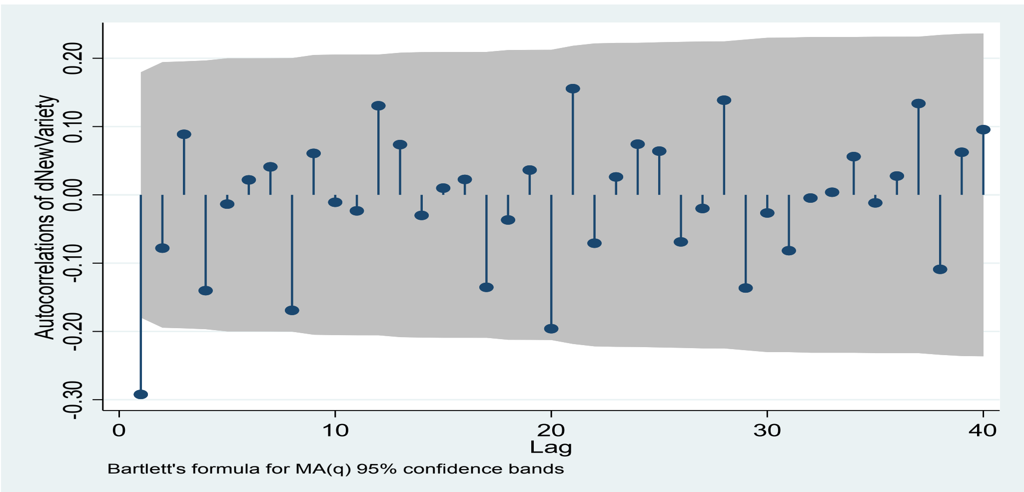

Figure 5: ACF Correlograms of the differenced Areca nut price series
Source: Authors processing using areca nut price series

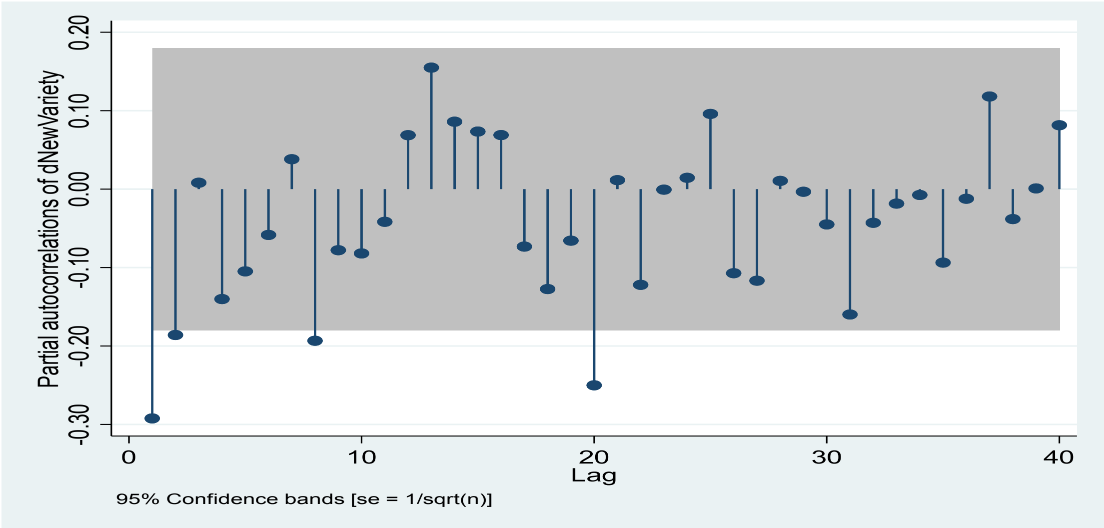

Figure 6: PACF Correlograms of the Areca nut price series
Source: Authors processing using areca nut price series

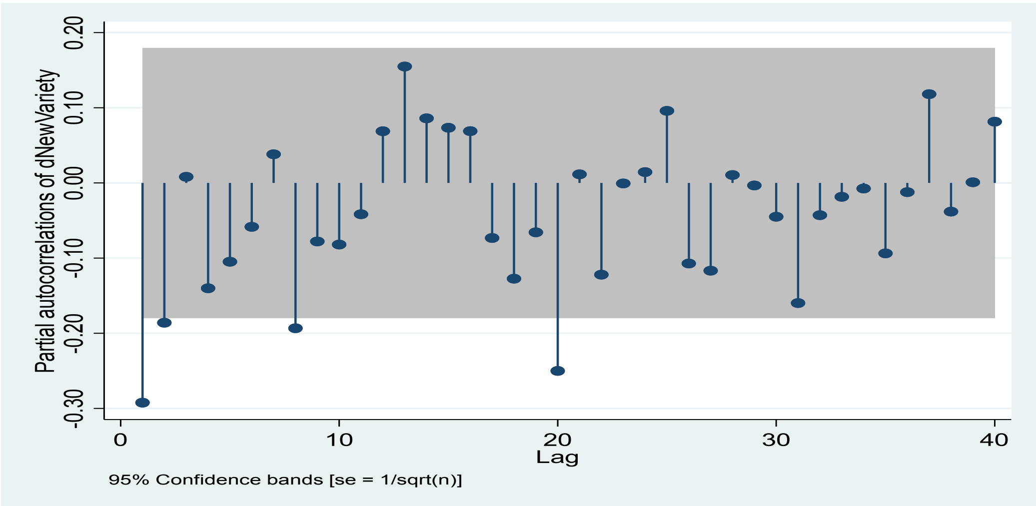

Figure 7: ACF correlograms of the differenced Areca nut price series
Source: Authors processing using areca nut price series

5. Identification of the model

Once the series is stationary, the next job is to identify whether it is an AR or MA process and to identify the p and q terms for the model. Many researchers (Sukiyono et al., 2018; Darekar and Reddy, 2017; Goswami, 2014; Nochai and TItida, 2006 and Ohyver and Pudjihastuti, 2018; Gujarati et al., 2009) have used and advised to observe the pattern of the ACF and PACF correlograms to identify p, q terms. Rule of thumb is that if the ACF of integrated series shows significant spikes in the higher lags, then we can consider that series as AR process. Further, if the 1st lag of PACF is positive, then it is advised to add an AR term to the model. In our analysis, the first lags of both ACF and PACF are negative; therefore, it is an MA process. The lags at which the ACF and PACF cut off are the number of terms to be considered for MA and AR respectively. Figure 5 and Figure 7 shows the ACF and PACF correlograms of the differenced series. PACF cuts off at 1st lag, and the 1st lag of PACF is negative;hence, it is an MA (1) process we can start with.(Gujarati et al., 2009) identifying the model is not accurate; with good experience, a good number of experiments are also important to arrive at a more accurate model. We have identified following 7 alternative models (1,1,1), (2,1,1), (3,1,1), (1,1,2), (2,1,2) (3,1,2) and (3,1,3) to estimate.

6. Estimation

We are using the first order differenced of Areca nut price series to estimate the ARIMA model. The purpose of estimation is to identify the most appropriate model from the above given 7 alternative models. For all the seven alternative models, we have run the ARIMA estimates along with Akaike's information criterion (AIC) and Bayesian (BIC) information criterion. (Gujarati et al., 2009) the appropriate model can be selected based on the following given estimates: 1. Most significant coefficients, 2.Lowest Volatility, 3.Highest log-likelihood, and 4.Lowest AIC and BIC. We have extracted above 5 estimates from our analysis output for all the 7 alternative models, and the same are tabulated below. Model (3, 1, 3) beats all other models with the highest number of significant coefficients (6) and minimum volatility (2512.64). The other two criteria are also in favour of model (3, 1, 3) with the highest log-likelihood of statistic and lowest AIC values. Model (1, 1, 2) has got the lowest BIC value, but all other criteria are in favour of the ARIMA model (3, 1, 3), which is AR (3), 1st difference, and MA (3). So, based on the 5-yardstick analysis, we have identified model (3, 1, 3) as the most ideal or appropriate model for estimation. Therefore, we are carrying the selected model (3, 1, 3) for the diagnostic check.

Table 1. Extracted statics from the ARIMA, AIC and BIC estimations

Differenced Areca nut price	(1,1,1)	(2,1,1)	(3,1,1))	(1,1,2)	(2,1,2)	(3,1,2)	(3,1,3)
Significant Coefficients	1	2	2	0	2	4	6
Volatility	2697.55	2651.88	2651.97	2625.92	2651.10	2607.80	2512.64
Log-Likelihoodod	-1102.33	-1100.51	-1100.49	-1099.83	-1100.36	-1099.28	-1096.89
AIC	2212.66	2211.01	2212.98	2207.67	212.74	2210.56	2207.77
BIC	2223.74	2224.87	2229.61	2218.75	2229.36	2227.18	2227.17

Source: Author's computations from differenced Areca nut price database

7. Diagnostic checking

Gujarati et al., (2009)for diagnostic checking of the ARIMA model, estimate the residuals for selected ARIMA model and obtain ACF, PACF correlograms for those estimated residuals. From the ACF and PACF correlograms of residuals, we can say that residuals are random. Further, all the estimated ACF and PACF are within the 95% confidence bands. Hence none of these is individually statistically significant. Therefore, the ARIMA model (3, 1, 3) is an appropriate model to forecast, and it may not be necessary to check for some other ARIMA model.

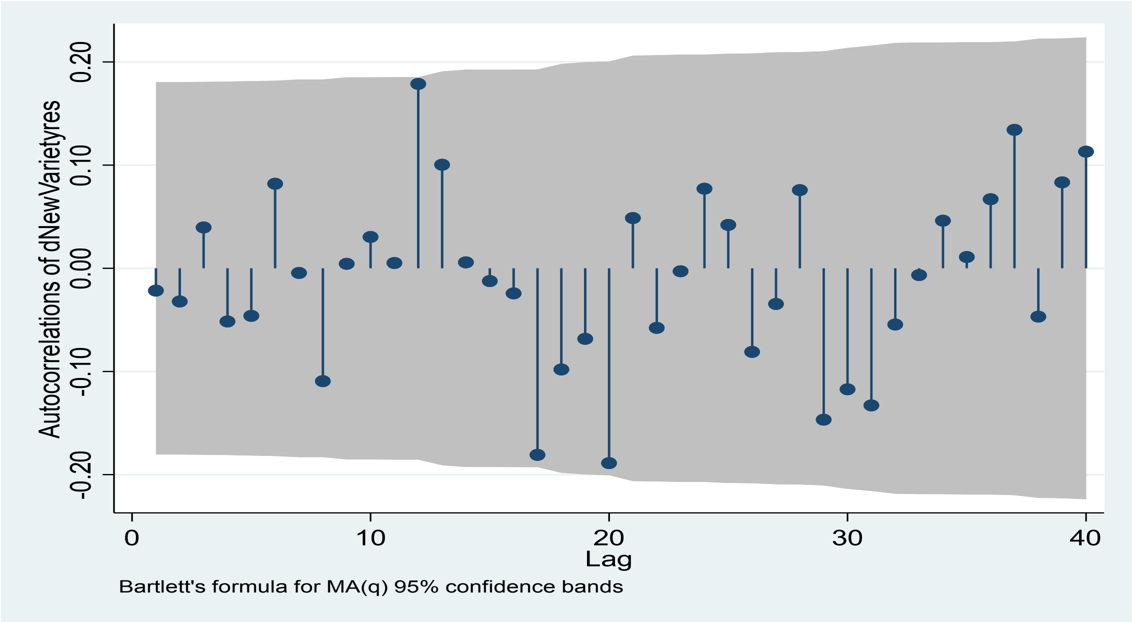

Figure 8: ACF Correlograms of the ARIMA 3, 1, 3 residuals
Source: Authors processing using Areca nut price series

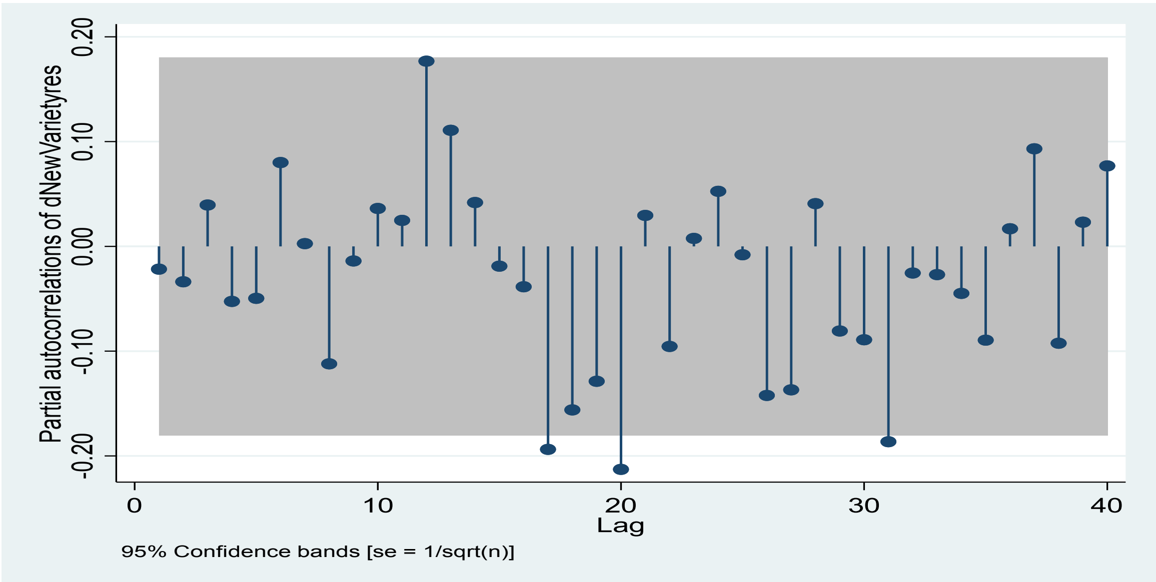

Figure 9: PACF Correlograms of the ARIMA 3, 1, 3 residuals
Source: Authors processing using areca nut price series

8. Conclusions

This paper aimed to develop an appropriate forecast model for monthly Areca nut price in Karnataka, India. With the help ofACF and PACF correlograms, we have identified seven tentative models. From the estimates of Box – Jenkins methodology for all the tentative models, ARIMA (3, 1, 3) model is considered as an appropriate model to forecast the price for new variety Areca nut in Karnataka, India. That is autoregressive (AR) *p*is 3, differencing order (I) d is 1, and Moving Average (MA) d is 3. Because of cross border trading, uncertainty and price risk are increasing in the agricultural commodities market. This type of forecasting model can help Areca nut growers, traders, and policymakers to take proper decisions in the volatile market. As there is no much industrial demand for the commodity areca nut, there is no such evidence from the past studies concerning price determinants for this commodity. However, a good number of studies have mentioned about increasing import and export activities with this commodity; hence, this opens the door for future studies on the impact of exchange rates on the price of commodity areca nut.

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APPENDIX

Estimations for ARIMA (1, 1, 1) model with AIC and BIC values

ARIMA regression
Sample: 2009m3 - 2018m12 Number of obs = 118
Wald chi2(2) = 32.57
Log-likelihood = -1102.328 Prob > chi2 = 0.0000

D. dNewVariety	Coef.	OPG Std. Err.	z	P>z	[95% Conf. Interval	
dNewVariety _ cons	-2.83477	7.915106	-0.36	0.72	-18.3481	12.67856
ARMA						
ar						
L1.	-0.28546	0.06129	-4.66	0	-0.40558	-0.16533
ma						
L1.	-1	976.5341	0	0.999	-1914.97	1912.972
/sigma	2697.549	1317179	0	0.499	0	2584320
Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	118	.	-1102.33	4	2212.657	2223.739

Source: Authors estimations using 1st order differenced Areca nut price series.

Estimations for ARIMA (2, 1, 1) model with AIC and BIC values

ARIMA regression
Sample: 2009m3 - 2018m12 Number of obs = 118
Wald chi2(3) = 41.46
Log likelihood = -1100.507 Prob > chi2 = 0.0000

D. dNewVariety	Coef.	OPG Std. Err.	z	P>z	[95% Conf. Interval	
dNewVariety _ cons	-2.59149	7.053018	-0.37	0.713	-16.4152	11.23217
ARMA						
ar						
L1.	-0.33882	0.069743	-4.86	0	-0.47551	-0.20212
L2.	-0.1766	0.086891	-2.03	0.042	-0.34691	-0.0063
ma						
L1.	-1.00001	327.2587	0	0.998	-642.415	640.4152
/sigma	2651.879	434001.6	0.01	0.498	0	853279.4
Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	118	.	-1100.51	5	2211.014	2224.867

Source: Authors estimations using 1st order differenced Areca nut price series.

Estimations for ARIMA (3, 1, 1) model with AIC and BIC values

ARIMA regression
Sample: 2009m3 - 2018m12 Number of obs = 118
Wald chi2(3) = 41.46
Log likelihood = -1100.507 Prob > chi2 = 0.0000

D.		OPG				
dNewVariety	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
dNewVariety_cons	-2.612174	7.186199	-0.36	0.716	-16.69687	11.47252
ARMA						
ar						
L1.	-0.335782	0.0836918	-4.01	0	-0.499815	-0.171749
L2.	-0.1706765	0.1266299	-1.35	0.178	-0.4188665	0.0775135
L3.	0.0158937	0.1134692	0.14	0.889	-0.2065018	0.2382893
ma						
L1.	-1.000002	1122.57	0	0.999	-2201.197	2199.197
/sigma	2651.967	1488571	0	0.499	0	2920198
Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	118	.	-1100.492	6	2212.985	2229.609

Source: Authors estimations using 1st order differenced Areca nut price series.

Estimations for ARIMA (1, 1, 2) model with AIC and BIC values

ARIMA regression
Sample: 2009m3 - 2018m12 Number of obs = 118
Wald chi2(2) = 4.57
Log likelihood = -1099.834 Prob > chi2 = 0.1017

D.		OPG				
dNewVariety	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
dNewVariety_cons	-2.580705	4.348544	-0.59	0.553	-11.10369	5.942284
ARMA						
ar						
L1.	0.3891661	0.2047792	1.9	0.057	-0.0121936	0.7905259
ma						
L1.	-1.739812	1045.237	0	0.999	-2050.367	2046.888
L2.	0.739811	773.3121	0	0.999	-1514.92	1516.404
/sigma	2625.917	1372216	0	0.499	0	2692120
Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	118	.	-1099.83	4	2207.668	2218.751

Source: Authors estimations using 1st order differenced Areca nut price series.

Estimations for ARIMA (2, 1, 2) model with AIC and BIC values

ARIMA regression
Sample: 2009m3 - 2018m12 Number of obs = 118
Wald chi2(4) = 249.11
Log likelihood = -1100.368 Prob > chi2 = 0.0000

D. dNewVariety	Coef.	OPG Std. Err.	z	P>z	[95% Conf.	Interval]
dNewVariety_ cons	-2.79078	7.895314	-0.35	0.724	-18.2653	12.68375
ARMA						
ar						
L1.	-1.10913	0.200152	-5.54	0	-1.50142	-0.71684
L2.	-0.33225	0.076379	-4.35	0	-0.48195	-0.18255
ma						
L1.	-0.18018	190.2168	0	0.999	-372.998	372.6379
L2.	-0.8198	156.021	-0.01	0.996	-306.615	304.9758
/sigma	2651.105	252123.8	0.01	0.496	0	496804.7
Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	118	.	-1100.37	6	2212.736	2229.36

Source: Authors estimations using 1st order differenced Areca nut price series.

Estimations for ARIMA (3, 1, 2) model with AIC and BIC values

ARIMA regression
Sample: 2009m3 - 2018m12 Number of obs = 118
Wald chi2(5) = 1149.85
Log likelihood = -1099.278 Prob > chi2 = 0.0000

D. dNewVariety	Coef.	OPG Std. Err.	z	P>z	[95% Conf.	Interval]
dNewVariety_ cons	-2.59316	6.287986	-0.41	0.68	-14.9174	9.731072
ARMA						
ar						
L1.	-1.30052	0.089255	-14.57	0	-1.47545	-1.12558
L2.	-0.49523	0.107919	-4.59	0	-0.70674	-0.28371
L3.	-0.14301	0.094701	-1.51	0.131	-0.32862	0.042601
ma						
L1.	-0.00041	3.976551	0	1	-7.7943	7.793492
L2.	-0.99959	0.095026	-10.52	0	-1.18584	-0.81335
/sigma	2607.804	.	.	.	.	.
Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	118	.	-1099.28	6	2210.557	2227.181

Source: Authors estimations using 1st order differenced Areca nut price series.

Estimations for ARIMA (3, 1, 3) model with AIC and BIC values

ARIMA regression
Sample: 2009m3 - 2018m12 Number of obs = 118

Wald chi2(6) = 286776.02						
Log likelihood = -1096.888				Prob > chi2	=	0.0000
D.		OPG				
dNewVariety	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
dNewVariety _ cons	-4.08792	1.821238	-2.24	0.025	-7.65748	-0.51836
ARMA						
ar						
L1.	-0.3681	0.110512	-3.33	0.001	-0.5847	-0.1515
L2.	0.688512	0.142922	4.82	0	0.408391	0.968634
L3.	0.201207	0.109184	1.84	0.065	-0.01279	0.415205
ma						
L1.	-1.02412	0.140336	-7.3	0	-1.29918	-0.74907
L2.	-0.94976	0.144279	-6.58	0	-1.23255	-0.66698
L3.	0.975209	0.095458	10.22	0	0.788114	1.162303
/sigma	2512.645	.	.	.	.	.
Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	118	.	-1096.89	7	2207.775	2227.17

Source: Authors estimations using 1st order differenced Areca nut price series.