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Research Article

Predictive Analysis of Cotton and Turmeric Prices: Understanding its Influential Factors on the National Commodities and Derivatives Exchange.

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ABSTRACT

In the modern era of investing, it's become increasingly common for investors to manage diverse portfolios that involve a combination of equities, debt, currencies, and commodities. Recently, the commodities market has emerged as a popular choice among investors, leading to an uptick in research in this area. With many beneficiaries, including farmers, consumers, arbitragers, speculators, and industrialists, the commodities market experiences high traded volumes and constant demand and supply fluctuations. Agricultural commodities traded on the National Commodities and Derivatives Exchange of India have seen an increase in trading volume, contributing to price volatility and risk. Additionally, these commodities are subject to seasonality, as they are only traded during certain times of the year, making investment decisions even more challenging. However, tools such as derivatives can be used to hedge against risk and mitigate potential losses.

In order to hedge their investments effectively, investors must understand and be able to forecast future price trends of commodities and volumes. Fortunately, there are models available to aid investors in predicting future trends, such as Linear Regression, K-Nearest Neighbor (KNN), AutoRegressive Integrated Moving Average (ARIMA), and Long Short-Term Memory (LSTM).

This study anticipates the future prices of certain agricultural goods traded in India. After conducting literature reviews, we have determined that the ARIMA model is a reliable source for precise results. As a result, our study employs the ARIMA model to predict the future prices of Cotton and Turmeric traded on the NCDEX. We accomplished this by utilizing an analytical methodology with the ADF Econometrics model to verify stationarity. Our data was sourced from secondary sources available on the NCDEX website.

Our study anticipates that the prices of these commodities will remain stationary at the first-order difference. Meanwhile, the prices will be stationary at extremes at the second-order difference, indicating the suitability for a further predictive model. Based on information criteria, the models with the lowest AIC and BIC scores are deemed the most suitable for predicting the future prices of Cotton and Turmeric in India.

Key Words: Agricultural Commodities- Cotton and Turmeric, ADF, ARIMA.

INTRODUCTION

Investments have evolved towards diverse portfolios where investors manage various combinations involving equity, debt, currencies, and commodities. The commodities market has recently attracted multiple investors, enhancing the scope for excessive research. The commodities market includes the trade of crude oil, gold, agricultural commodities, etc. It has many beneficiaries, such as farmers, consumers, arbitragers, speculators, industrialists, etc., and is subjected to high traded volumes and constant demand and supply variations.

AGRI OPTIONS TRADED CONTRACTS AND TRADED VALUE		
Year	Traded Contracts in Lots	Total Value in Lakhs
2018	1,01,880	45,487
2019	5,835	2,477
2020	12,680	6,333
2021	18,455	12,385
2022	4,01,591	2,35,645

Table 1: Source, NCDEX, November 2022

AGRI OPTIONS TRADED CONTRACTS AND TRADED VALUE		
Year	Traded Contracts in Lots	Total Value in Lakhs
2018	10,85,080	7,43,884
2019	26,02,717	2,02,87,151
2020	27,89,713	2,86,78,355
2021	1,74,92,627	11,50,76,938
2022	7,19,48,102	56,91,73,112

Table 2: Source, MCX, 2022

Agricultural commodities traded on the National Commodities and Derivatives Exchange of India recently showed increased trade volumes in the commodities market. These volumes and trade lead to price volatility, which, in return, contributes to risk. Agricultural commodities face an additional risk of seasonality as these commodities are only traded in a particular season. Investment decisions can be difficult due to these risk factors and require tools to hedge the same. The risk can be hedged with the help of derivatives.
Derivatives derive their values from an underlying asset traded in the markets. These instruments are mainly traded to hedge the risk of loss in the actual market. The prices of the assets and commodities traded in the market usually follow a trend. This trend depends on the historical prices of the commodity or asset. The movement varies with time. Therefore, a trend analysis will help the investors or stakeholders analyse and forecast future prices. Models predicting future trends aid investors. For this purpose, there are models such as Linear regression, K-nearest neighbour (KNN), Auto-Regressive Integrated Moving Average (ARIMA) and Long Short-Term Memory (LSTM).
This study uses the prediction analysis of the commodities traded on the National Commodities and Derivatives Exchange using the AutoRegressive Integrated Moving Average (ARIMA) model.
The analysis focused on monthly Wholesale Price Index (WPI) data and near-month futures prices for five cash crops traded on two national-level commodity exchanges. The objective was to examine how inflation influences the future prices of these cash crops. The futures prices of Castor, Cotton, and Soybean were found to be responsive to changes in their respective wholesale prices. In contrast, the wholesale price of Cardamom was observed to be influenced by short-term changes in its futures price. Furthermore, the volatility in Turmeric futures prices was found to be solely dependent on deviations within the Turmeric market itself. (Dr. Sandeep Sehrawat, 2022)
The study analyzed India's agricultural commodity exports from 2000-01 to 2017-18, revealing significant growth in certain groups like cotton, cereals, meat, and spices. Notable export share increases were observed for rice, meat, spices, sugar, and cotton. However, some commodities experienced declining export shares. Revealed that Comparative Advantage improved for cotton, grapes, groundnuts, maize, potato, pineapples, and rice but declined for apple, coffee, cashew nuts, ginger, mangoes, oilseeds, onion, peas, tea, and wheat. The study also highlighted that price volatility discouraged farmer investments, posing a threat to long-term sustainability. (Dev Kapil, 2022)
This paper aims to investigate the rationale behind a commodity trading ban and assess whether commodity futures trading significantly impacts the volatility of commodity spot prices. Data from the NCDEX, spanning four quarters, focuses on three commodities: sugar, channa, and turmeric. Variables such as traded volume, traded value, and trade price are analysed using statistical tools, including correlation, regression, Granger Causality test, and the Garch model for volatility. Reliability analysis ensures the data's credibility. Results

indicate causality from volume to spot prices in two out of three commodities, while one commodity shows no such causality. Moreover, insufficient evidence supports that future markets contribute to higher inflation. (Singhal Shelly, 2011)
The study by (Devi Ambar Wati, 2020) shows that the ARIMA model is the best model to predict inflation and commodities prices in Indonesia. It also says forecasting is a valuable tool that provides an overview of future events, aiding decision-making processes. Accurate inflation forecasting can assist governments in creating effective economic and other policies. For governments, inflation forecasting serves as a bridge to determine the value of future inflation. The study aims to improve inflation forecasting in Indonesia and provide input for Bank Indonesia to consider policy-making.
The study (Bandyopadhyay, 2016) uses the ARIMA model to predict future gold prices in the Indian commodity market. It aims to mitigate the risk involved in the gold trade and to assist investors regarding the right time to buy and the right time to sell. This study assumes a perfectly linear pattern, and the ARIMA model was used to forecast the price of gold. It also suggests using non-linear forecasting methods with soft computing techniques to reduce white noise.
The analysis mainly focused on forecasting consumable goods using ARIMA, Neural networks and a combination of both, naming it a hybrid model. The study also compared the models and tested their accuracy. The SARIMA (Seasonal Autoregressive Integrated Moving Average) was also analysed as commodities are exposed to seasonality factors. The hybrid method that combined the ARIMA method for linear data and the neural network method for non-linear properties was expected to achieve the highest possible accuracy rate compared to the other techniques used individually. Nevertheless, the results of the data analysis showed that the neural network method had a better accuracy rate than the hybrid method and ARIMA. (Arian Dhini, 2015)
This paper focuses on predicting the market prices of soybeans as India is the world's fourth-largest oilseed producer. This study aims to forecast soybean prices before harvest to aid farmers in making selling and storage decisions. The study concludes that the proposed ARIMA model can predict the fluctuations in the prices of soybeans and explain the underlying seasonality. Farmers and traders can effectively use this model to make informed decisions about sowing and selling, thereby minimising the scope for speculation. (REDDY, 2017)
The paper's goal (V. Jadhav, 2017) is to showcase the effectiveness of price forecasting for agricultural products, specifically Paddy, Ragi, and Maize, in Karnataka, focusing on 2016. This demonstration relies on analysing time series data from 2002 to 2016 to validate the forecasting outcomes. The outcomes of ARIMA price forecasts convincingly highlight the efficacy of the ARIMA model as a robust tool for price forecasting. This is evident in the practical models showcasing forecasted prices for the year 2020.
This paper analyses fruit and vegetable prices in the Bengaluru region of Karnataka. To illustrate price prediction, the study employs seasonal ARIMA to forecast the prices of fruits and vegetables. The aim is to assist the public by providing advanced information, enabling them to strategize effectively if predicted prices are expected to rise in the coming months, facilitating measures to mitigate increases in fruit and vegetable prices. (Khosla, 2019)

OBJECTIVE:

1) To predict the future prices of turmeric and cotton traded at India's National Commodities and Derivatives Exchange.
2) To test the accuracy of the ARIMA model used to predict the future prices of Turmeric and Cotton.
3) To identify the factors influencing future price prediction through a literature survey.

RESEARCH METHODOLOGY

The scope of the study is restricted to predicting the future prices of Turmeric and Cotton as they are traded on NCDEX for a considerably long duration. The data is collected from the website, and the study is based on secondary data sources. The type of data used for analysis is time-series data. The timeline used for calculation is ten years (1^{st} April 2013 to 30^{th} November 2023).
The data obtained is raw and needs to be tested for normality and stationarity. For this purpose, probability and Jarque Bera tests were conducted to identify normality and skewness. Further, the data will undergo differencing processes to eliminate irregularities, seasonality, and trends. Additionally, the data is checked for stationarity with the assistance of the ADF test (Augmented Dicky Fuller test). Durbin-Walton statistic is used to check auto-correlation.
The ARIMA model is used for Prediction analysis, and the Akaike Information Criterion and Bayesian Information Criterion are used to choose the best and most accurate model for prediction. R-squared value is used to identify the goodness of fit.

ANALYSIS

The analysis was conducted separately for turmeric and cotton; the findings and interpretations are mentioned below:

COTTON:

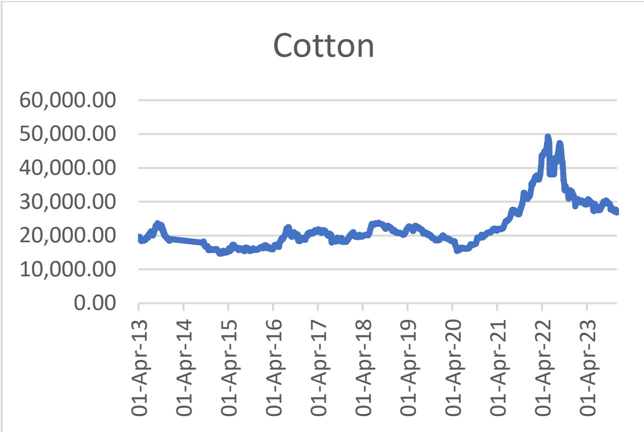

Figure 1: Graph showing the original data trend

The above graph shows the trend of the closing prices of cotton at NCDEX. The graph indicates a spike, which paves the foundation for the differencing process.
The following hypothesis is generated to test the level of significance.
Null Hypothesis: Data for Cotton is not significant
Alternate Hypothesis: Data for Cotton is significant

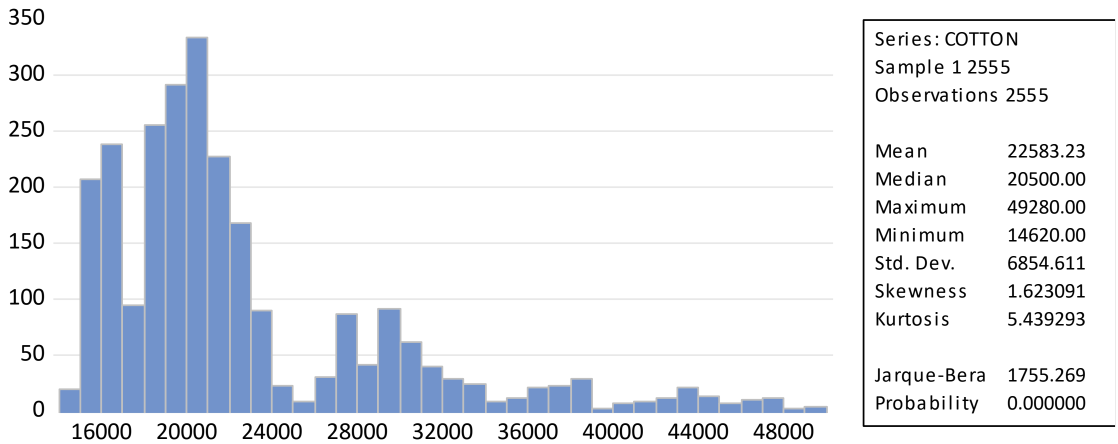

Figure 2: Graph showing normality and descriptive statistics

From the graph, we can observe that the data is right-skewed. A probability of less than 0.05 indicates that the data is significant and can be used for further study. Therefore, the null hypothesis is rejected, and the alternate hypothesis is accepted.

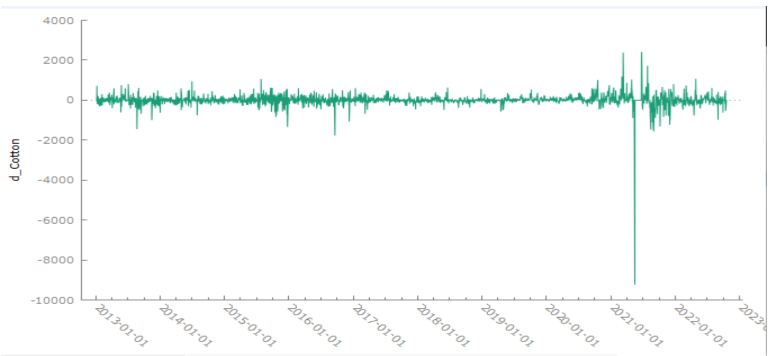

Figure 3: After the first level of differencing

The differencing at the first level makes the data ready for the stationarity test.
For the stationarity test, the Augmented Dickey-Fuller test was conducted, and the hypotheses are as follows:
Null Hypothesis: Cotton has a unit root
Alternate Hypothesis: Cotton does not have a unit root.

Null Hypothesis: D(COTTON) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=26)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-30.92300	0.0000
Test critical values:	1% level	-3.961640	
	5% level	-3.411568	
	10% level	-3.127651	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(COTTON,2)
Method: Least Squares
Date: 12/11/23 Time: 10:11
Sample (adjusted): 4 2555
Included observations: 2552 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(COTTON(-1))	-0.809838	0.026189	-30.92300	0.0000
D(COTTON(-1),2)	-0.081418	0.019722	-4.128205	0.0000
C	0.810721	11.62248	0.069755	0.9444
@TREND("1")	0.001096	0.007877	0.139090	0.8894

R-squared	0.445081	Mean dependent var	-0.286050
Adjusted R-squared	0.444428	S.D. dependent var	393.2737
S.E. of regression	293.1332	Akaike info criterion	14.20070
Sum squared resid	2.19E+08	Schwarz criterion	14.20986
Log likelihood	-18116.09	Hannan-Quinn criter.	14.20402
F-statistic	681.2213	Durbin-Watson stat	2.005999
Prob(F-statistic)	0.000000		

Time series data often exhibits non-stationary behaviour, making it less suitable for predictive analysis. Tests were conducted to address this issue and enhance the data's suitability for prediction. The figure above presents the results of the Augmented Dickey-Fuller (ADF) test, revealing a probability value below 5%, signifying the statistical significance of the data and supporting its appropriateness for predictive modelling. To achieve stationarity, the original data underwent differencing at one lag. Additionally, the Durban-Watson statistic was considered as another indicator, yielding a value close to 2 (less than 4). This result further confirms the stationarity of the index prices, reinforcing the data's readiness for predictive analysis.

Model 11: ARIMA, using observations 2013-04-02:2023-01-13 (T = 2554)
Dependent variable: (1-L) Cotton
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	3.07559	8.94212	0.3439	0.7309	
phi_1	0.834418	0.0449851	18.55	<0.0001	***
theta_1	−0.743738	0.0545340	−13.64	<0.0001	***

Mean dependent var	3.073610	S.D. dependent var	296.2412
Mean of innovations	−0.042926	S.D. of innovations	292.2477
R-squared	0.998184	Adjusted R-squared	0.998183
Log-likelihood	−18124.59	Akaike criterion	36257.19
Schwarz criterion	36280.57	Hannan-Quinn	36265.67

		Real	*Imaginary*	*Modulus*	*Frequency*
AR					
	Root 1	1.1984	0.0000	1.1984	0.0000
MA					
	Root 1	1.3446	0.0000	1.3446	0.0000

Figure 4: ARIMA for Cotton

Various AutoRegressive (AR) and Moving Average (MA) models, along with an integration level of 1 obtained through Augmented Dickey-Fuller (ADF) testing, were computed. The selection criteria were based on the information criteria of Akaike (AIC) and Schwarz (BIC). The model with the lowest AIC and BIC values of

36257.19 and 36280.57 was identified as 1,1,1. This indicates that the 1,1,1 model is considered the best among all other combinations for forecasting the future price of the Index.

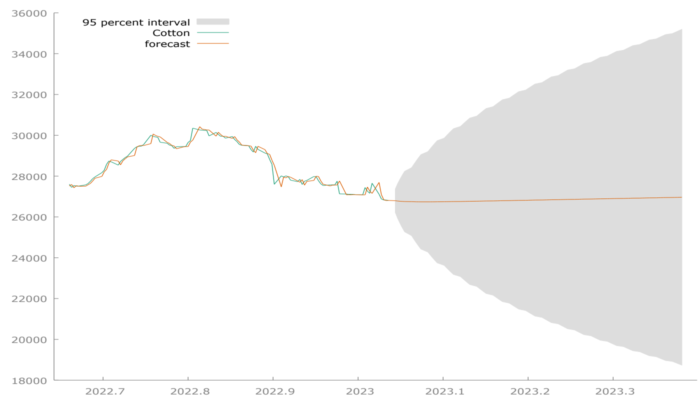

Figure 5: Graph showing forecasted prices for Cotton

The provided graph illustrates the predicted values of Cotton. Notably, there are minimal differences between the prices of actual and projected values in the initial years, suggesting that the predicted values closely align with the actuals.

TURMERIC

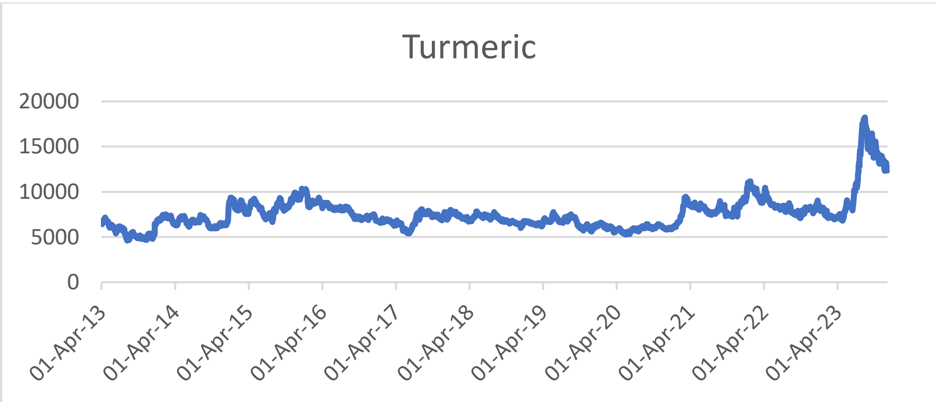

Figure 6: Graph showing closing prices of Turmeric at NCDEX

The above graph shows the trend of the closing prices of cotton at NCDEX. The graph indicates a spike, which paves the foundation for the differencing process.
The following hypothesis is generated to test the level of significance.
Null Hypothesis: Data for Cotton is not significant
Alternate Hypothesis: Data for Cotton is significant

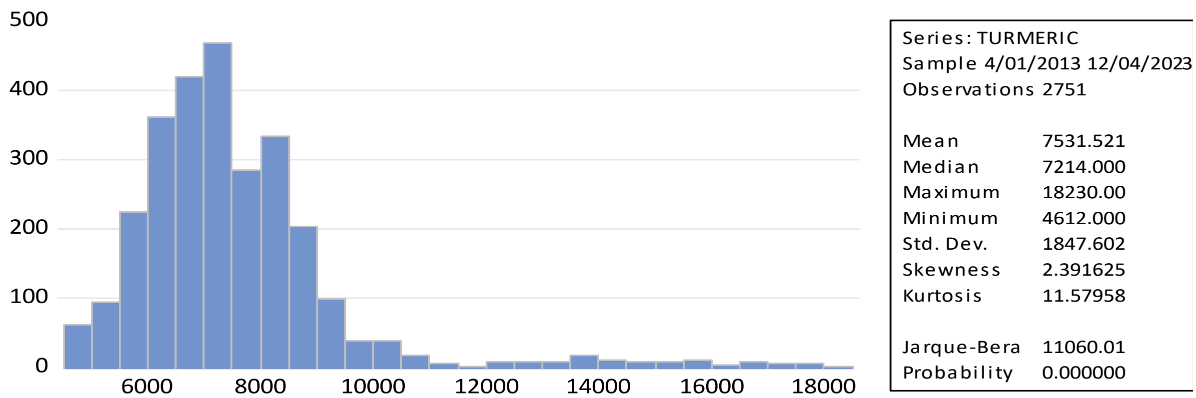

Figure 7:Graph showing normality and descriptive statistics

From the graph, we can observe that the data is right-skewed. A probability of less than 0.05 indicates that the data is significant and can be used for further study. Therefore, the null hypothesis is rejected, and the alternate hypothesis is accepted.

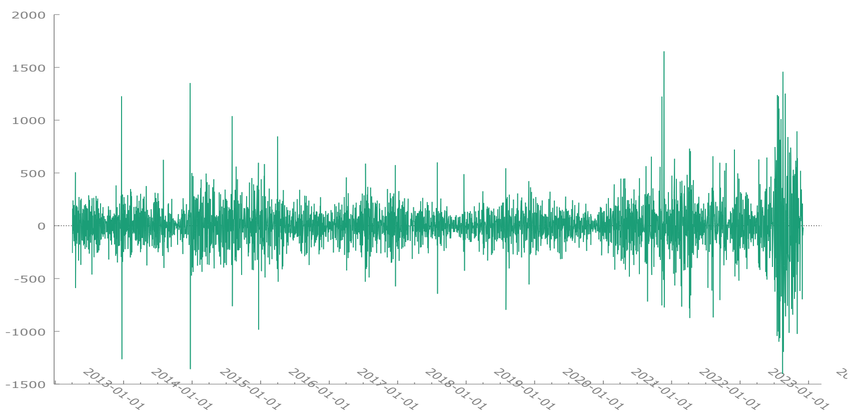

Figure 8: After two lags differencing

The differencing at the second level makes the data ready for the stationarity test.
For the stationarity test, the Augmented Dickey-Fuller test was conducted, and the hypotheses are as follows:
Null Hypothesis: Turmeric has a unit root
Alternate Hypothesis: Turmeric does not have a unit root.

Null Hypothesis: D(TURMERIC,2) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 14 (Automatic - based on SIC, maxlag=26)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-22.44762	0.0000
Test critical values:	1% level	-3.961399	
	5% level	-3.411451	
	10% level	-3.127581	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(TURMERIC,3)
Method: Least Squares
Date: 12/11/23 Time: 10:14
Sample (adjusted): 4/20/2013 12/04/2023
Included observations: 2734 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(TURMERIC(-1),2)	-8.024383	0.357471	-22.44762	0.0000
D(TURMERIC(-1),3)	6.140074	0.350282	17.52896	0.0000
D(TURMERIC(-2),3)	5.280297	0.337987	15.62277	0.0000
D(TURMERIC(-3),3)	4.511148	0.320783	14.06293	0.0000
D(TURMERIC(-4),3)	3.795892	0.299695	12.66584	0.0000
D(TURMERIC(-5),3)	3.115323	0.274986	11.32902	0.0000
D(TURMERIC(-6),3)	2.449352	0.247175	9.909392	0.0000
D(TURMERIC(-7),3)	1.901257	0.217386	8.746006	0.0000
D(TURMERIC(-8),3)	1.426699	0.186401	7.653930	0.0000
D(TURMERIC(-9),3)	1.016460	0.154894	6.562314	0.0000
D(TURMERIC(-10),3)	0.747578	0.124154	6.021399	0.0000
D(TURMERIC(-11),3)	0.548873	0.094579	5.803304	0.0000
D(TURMERIC(-12),3)	0.364983	0.066622	5.478379	0.0000
D(TURMERIC(-13),3)	0.233054	0.040901	5.698051	0.0000
D(TURMERIC(-14),3)	0.075920	0.019211	3.952007	0.0001
C	-0.169877	6.410223	-0.026501	0.9789
@TREND("4/01/2013")	-0.000113	0.004025	-0.028015	0.9777

R-squared	0.813291	Mean dependent var	-0.190929
Adjusted R-squared	0.812192	S.D. dependent var	383.2334
S.E. of regression	166.0812	Akaike info criterion	13.06903
Sum squared resid	74942948	Schwarz criterion	13.10580
Log likelihood	-17848.36	Hannan-Quinn criter.	13.08232
F-statistic	739.6930	Durbin-Watson stat	2.001432
Prob(F-statistic)	0.000000		

Figure 9: Augmented Dickey-Fuller test for Turmeric

The figure above presents the results of the Augmented Dickey-Fuller (ADF) test, revealing a probability value below 5%, signifying the statistical significance of the data and supporting its appropriateness for predictive modelling. To achieve stationarity, the original data underwent differencing at two lags. Additionally, the Durban-Watson statistic was considered as another indicator, yielding a value close to 2 (less than 4). This result further confirms the stationarity of the index prices, reinforcing the data's readiness for predictive analysis. Therefore, the alternate hypothesis is accepted.

Model 15: ARIMA, using observations 2013-04-03:2023-12-04 (T = 2749)
Dependent variable: (1-L) ^2 Turmeric
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	0.00305621	0.00420687	0.7265	0.4675	
theta_1	−0.930340	0.00194460	−478.4	<0.0001	***
theta_2	−0.0696600	0.00178649	−38.99	<0.0001	***

Mean dependent var	−0.114223	S.D. dependent var	224.3029
Mean of innovations	−0.290039	S.D. of innovations	163.7393
R-squared	0.992165	Adjusted R-squared	0.992162
Log-likelihood	−17919.72	Akaike criterion	35847.43
Schwarz criterion	35871.11	Hannan-Quinn	35855.99

		Real	*Imaginary*	*Modulus*	*Frequency*
MA					
	Root 1	1.0000	0.0000	1.0000	0.0000
	Root 2	-14.3554	0.0000	14.3554	0.5000

Figure 10: ARIMA for Turmeric

Various AutoRegressive (AR) and Moving Average (MA) models, along with an integration level of 1 obtained through Augmented Dickey-Fuller (ADF) testing, were computed. The selection criteria were based on the information criteria of Akaike (AIC) and Schwarz (BIC). The model with the lowest AIC and BIC values of 35847.43 and 35871.11 was identified in the order of 0,2,2. This indicates that the 0,2,2 model is considered the best among all other combinations for forecasting the future price of the Index.

The provided graph illustrates the predicted values of Turmeric. There are minimal differences between the prices of actual and projected values in the initial years, suggesting that the predicted values closely align with the actuals.

FINDINGS

Commodity prices on the National Commodity & Derivatives Exchange (NCDEX) in India are affected by several factors, including supply and demand dynamics, global market trends, government policies, weather conditions, geopolitical events, and macroeconomic factors. These factors impact the prices of commodities such as turmeric and cotton.
Due to the increasing importance of commodity prices and growing demand from investors, understanding the factors that affect commodity prices has become essential before investing in such products. These factors ultimately influence commodity demand and supply rates, impacting prices (Chambers, 2010). Generally, we can categorise the factors that affect commodity prices into the following categories

Supply and Demand Dynamics: The principle of supply and demand is essential in determining commodity prices. If the supply of turmeric or cotton is more than the demand, prices tend to decrease, and if the demand is more than the supply, prices tend to increase. The supply is influenced by crop yields, production forecasts, and inventory levels, while consumption patterns, export demand, and industrial usage affect the demand.
Weather Conditions: Agricultural commodities such as turmeric and cotton are highly affected by weather conditions. Adverse weather events like droughts, floods, or pest infestations can significantly impact crop yields, leading to shortages in supply and price spikes. Conversely, favourable weather conditions can increase yields and result in surplus supply, which puts downward pressure on prices. It is important to note that weather plays a crucial role in determining the prices of these commodities.
Global market Trends: Commodity prices on NCDEX are subject to global market trends. Several factors influence these prices, including international demand, production levels in major producing countries, currency exchange rates, and trade policies. For example, a sudden increase in cotton demand from major textile manufacturing countries like China can drive up prices on NCDEX.
Government Policies and Regulations: Government policies and regulations, such as trade policies, import/export duties, subsidies, and minimum support prices (MSPs), have a considerable impact on commodity prices. For example, the Indian government's decision to alter MSPs for turmeric or cotton can influence farmer decisions, production levels, and market prices.
Macro-Economic Factors: Macro-economic factors such as inflation, interest rates, exchange rates, and overall economic growth can indirectly impact commodity prices. For instance, a strong economy can increase consumer spending on textiles, thereby boosting demand and prices of cotton.
Geopolitical Events: Geopolitical tensions, conflicts, and trade disputes have the potential to disturb the supply chains and transportation routes and create market uncertainties that can affect commodity prices.

Trade wars, sanctions, or political instability in major producing or consuming regions can cause a ripple effect on NCDEX prices.
Speculative Activity: Speculative activity in commodity futures markets can influence prices as investors, hedge funds, and institutional traders buy or sell futures contracts based on their expectations of future prices, which may not be related to supply and demand fundamentals.
This does not help the farmers sell at the right price. These factors make the price of a product highly volatile. This issue prevails in the market due to traders' and investors' unawareness of market trends and product pricing. Sometimes, the prices quoted by the farmers are at a higher or lower rate. (Kumar, 2020)

RESULTS AND DISCUSSION

The right-skewed distribution of time series data for cotton suggests significance, with a probability less than 0.05, allowing for further in-depth analysis. Consequently, the null hypothesis is rejected in favour of the alternate hypothesis.
Augmented Dickey-Fuller (ADF) test results for cotton demonstrate a probability below 5%, affirming the statistical significance of the data and validating its suitability for predictive modelling. Acceptance of the alternate hypothesis indicates the absence of a unit root in the cotton data.
The 1,1,1 model, with AIC and BIC values of 36257.19 and 36280.57, respectively, emerges as the optimal choice among various combinations for forecasting the future price of cotton.
The significance of turmeric data, with a probability less than 0.05, supports its usability for further analysis. Consequently, the null hypothesis is rejected in favour of the alternate hypothesis.
The ADF test, revealing a probability below 0.05 and a Durbin-Watson test value of 2.001432, indicates that turmeric data lacks a unit root, making it suitable for predictive modelling.
The 0,2,2 model, with the lowest AIC and BIC values of 35847.43 and 35871.11, respectively, is identified as the most suitable among all combinations for forecasting turmeric.
Predicted values for cotton using ARIMA (1,1,1) and turmeric using ARIMA (0,2,2) closely align with the actual values, indicating the models' effectiveness in capturing the underlying patterns in the data.
The R-squared test shows a value close to 1, proving the model's accuracy in both cases. Therefore, the prediction model is accurate.
The prices of turmeric and cotton on NCDEX are influenced by various factors that interact in complex ways. Traders and investors must carefully analyse these factors and their interplay to make informed decisions in commodity markets.
It is crucial to understand the specific dynamics of each commodity, including seasonal patterns, storage costs, and quality variations, to develop successful trading strategies.

CONCLUSION

The predictive analysis conducted for the future prices of cotton and turmeric reveals valuable insights into potential market trends. It is crucial to recognise that predicting commodity prices involves inherent uncertainties due to various factors such as weather conditions, geopolitical events, and market dynamics. Nevertheless, the analysis provides a foundation for informed decision-making.
Market participants need to consider potential risks associated with unforeseen events. Continuous monitoring of the market landscape and re-evaluation of predictive models will be essential for making agile and informed decisions in response to changing circumstances. Additionally, stakeholders should keep abreast of new data inputs and advancements in predictive analytics to refine and enhance future forecasting models.
This paper can be helpful for intermediaries, particularly farmers, as it can help them determine the price of their products. It can also help them understand how the value of their product may change based on price fluctuations in other states. (Kumar, 2020)

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