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Forecasting Volatility of Crude oil Prices using Box-Jenkins's Autoregressive Moving Average: Evidence from Indian Chemical Industry

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***Abstract:** The current paper deals with to forecast volatility in crude oil prices in Indian economy. In the current study volatility is measured through change in monthly crude oil prices per barrel. The monthly data of crude oil price have taken from January 1995 to May, 2017. The different unit root tests are applied to test check change in crude oil price series is stationary or non stationary. Box-Jenkins's Autoregressive Moving Average of Box-Jenkins methodology has been used for developing a forecasting model. Minimum Akaike Information Criteria (AIC) has been opted to arrive at fit good ARMA model. According to this criteria (4, 3)(0,0) was observed as one of the best model to predict the volatility in future crude oil prices. Forecasted volatility in prices may be utilized for calculating future spot price and hedging future risk. Moreover, forecasted prices volatility of crude oil will also beneficial to oil companies, policy makers for formulating different economic policies and taking some crucial economic decision.*

***Key words:** Akaike Information Criteria, Augmented Dickey Fuller, Philips Perron Test.*

***JEL Classification:** C22, C82, C53*

I. INTRODUCTION

Energy resources including crude oil in chemical industry are really give force for the survival and growth of particular economy. India remains always dependent for crude oil on the Middle East countries. Rising trends of crude oil prices in chemical industry affect significantly the various economic activities of India. There are many terrible affects associated with the rising prices of crude oil to India, first increase in the crude oil price may affect balance of payment of country and second increased prices of crude oil in chemical industry affect Indian currency adversely, as India is required to make payment for import of crude oil in US dollars. Increased prices of petroleum products definitely increase transportation cost which result increase in the price of every product. Increased prices of crude oil lead to more payment as well as more demand of US dollars in country which lead to increase in the exchange of US dollar. Due to change in life style, increase in income as well as credit facilities there is much increase in number of vehicles in the country year by year.

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It results more demand of petroleum products in the country and consequently more import of crude oil. Rising prices of crude oil in chemical industry also affect various economic activities e.g., cost of production may increase due rising prices of petroleum products. It further leads to increase inflation in the economy.

Due to high inflation in economy, Indian companies may lose international price competitiveness. Due to these numbers of reasons forecasting of crude oil prices by some appropriate method may assist business operations and government policymaking. There are various risks prevail in the international market which ultimately affect the prices of crude oil in India. These risks can be categorized such as currency risk, country risk and geo political risk etc. As in the current period, we cannot ignore the importance energy resources for growth of economy. Rising prices of crude oil are the driving force of inflation which affects economy adversely. It is much essential for the policymakers to forecast prices of crude oil with due diligence.

From the crude oil supply perspective, the production of crude oil is concentrated in the hand of some Middle East countries. Emerging economies India, China, Russia, (and Brazil had a similar economic phase during the early stage of the 21st century. It shows fast growth during the first decade, post-2010 much slower growth. These countries increased the prices of oil in 2008 with their voracious demand and later assisted to lower down the prices in 2014 by demanding much less [7]. India's oil per capita oil consumption is 1.2 per barrels which is expected to increase to 1.5 barrels per year by 2022. As in many developing countries, several families are moving to higher scale income and consequently they buy first car. In the forecasted period, this will certainly be gasoline-fuelled [15]. Rise in oil prices has a significant impact on growth, inflation, current account deficit and fiscal imbalance. In such a scenario, there is a risk of further tightening in policy rates [12]. The concern over crude oil prices stalks from India's energy import bill of around 150 US billion dollars and it is predicted to reach three hindered US billion dollars by 2030 [1].

II. INDIAN CHEMICAL INDUSTRY AND CRUDE OIL PRICES

The decrease in oil prices since the mid of 2014 was a major setback to the global chemical industry. Many entrepreneurs and businessman were not aware of the enormity and speed of the impact on their businesses.

Frequent changes in the oil demand and supply at the global level expected to worsen the volatility of crude oil prices and enhance the chances of oil price jolt. Global chemical companies required to widen the organizational alertness to get ready for coming jolt and take quick actions when they arise [13]. India attained the major benefits of the decline in the crude oil prices at the international level during the past few years. It helped to lower down the inflation and increase in the gross domestic product (GDP) of the country. Chemicals are a critical input for several end-use consumer industries. The fortunes of the chemicals industry have long intertwined with crude oil prices and lower crude prices should benefit chemicals companies, which use crude oil or its derivatives as key ingredients in making the various products [2].

III. LITERATURE REVIEW

In this section, the review literature includes the different techniques used at the international to predict the crude oil prices and model dealing with volatility in crude oil prices. [21] Developed the mean-reverting process (MRP) model by applying the log-normal diffusion process to become aware of the sequence of volatility. There were many shortcomings in this model and then he suggested the mean-reverting jump-diffusion model for predicting the past and stochastic price movements. This model was not able to capture the prices as commonly not reverting to the mean consequent to high ups and downs [3]. The framework for computing or measuring the ups do not have predetermined values and deviation often remains between the mean reversion rates of jumps and volatility in general prices. In nutshell, we can say that the mean-reverting jump-diffusion model was not suitable to forecast future volatility in prices [25]. [23] Investigated the long term behaviour of coal, crude oil and natural gas prices by taking the database of 127 years (1887-1996). He analyses the estimation ability of the model with adding mean reversion to a deterministic linear trend. The results come out with findings that model with specification of find out the linear trend give best estimate of all energy resources. [24] used a shifting trend model with autoregressive method in error terms. He also used database of 127 years which covers the time period of same years as used by [23]. He consolidated the model with autoregressive and martingale hypothesis models and concludes that the result from the blend of models outperforms the single model. [27] and [28] carried out ARIMA approach to develop a model of crude oil price.

The out-of-sample forecasting results pointed out that the linear ARIMA model displays the worst prediction capability as compare with the nonlinear artificial neural network. [29] Tried to predict WTI crude oil prices with the help ARIMA method. Later, they compared the results with the support vector machine (VSM) and artificial neural networks (ANN) techniques. They discovered that last two methods (VSM and ANN) outperform as compare to ARIMA model. [11] employs ARIMA model for forecasting short and long time horizon. He uses day to day natural gas and crude oil prices prevailing in Dubai during last 12 years i.e., 1994 to 2005. The results confirmed that for very small period sphere forecast, the ARIMA model show best results as compare to ANN and VSM approaches [29]. [31] Conducted studies using survey and secondary data driven methods. They tried to investigate the relationship between crude oil prices and economic variables, econometric and intelligent computing models to predict future prices of crude oil. There was one more research which carried out by reviewing the researches of last two decades. It was a comprehensive survey and covered the diverse previous techniques and some results and experiments are demonstrated with main focus on essential steps required when forecasting oil prices [30]. [6] Conducted a comprehensive review of the existing theoretical literature that has been done by applying computational intelligence algorithms to predict prices of crude oil. This paper discover that conventional techniques used for crude oil forecasting are still more relevant They also discovered that the combination of wavelet analysis (WA) and computational intelligence techniques (CIT) is fetching unmatched interest from all such researchers who are carrying out studies to predict the prices or volatility in crude oil prices. An accurate forecasting price of crude oil help in the prediction of demand and supply of energy sources and brings stability in the market for petroleum products. [14] Found that uncertainties in oil price have vital impact on investment decisions and on economic indicators of the economy.

Hence it is required to help business operation and policy making by suggesting most accurate method to forecast future crude oil prices. They conducted research by taking monthly data 346 sets of observation (1984-2012) and proposed an modern projection technique through using the long-term quadratic sine-curve trend model for predicting the oil prices during the time period of 2013–2025. Results demonstrated that at global market crude oil price would be 120 to 150 US dollar per barrel under normal condition during the time period of 2013 to 2025 respectively. The findings of the study have great significance to business operators, investors, policy decisions, management and governments. [17] advocated that the quadratic function model developed through regression analysis represents the notion of an arc over space. They observed that this model leads to the better capability to forecast the key sources, dependent and demand for natural resources. The projected quadratic function model is shown by the equation:

$$Y_t = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \varepsilon_t$$

In the above equation "Yt" shows the actual crude oil prices at times "t" and "t" itself represents the time element. Whereas, "εt" represents the error term in the proposed model

The numerous studies already conducted are related to assessing the predictive powers of models to forecast the future crude oil prices [32] and to predict the volatility in the oil prices [10]. There are also some other studies which develop effective models to forecast future prices of crude oil. It is remarkable that [25] proposed a trend reverting jump and dip diffusion model for a longer time horizon. This model was intended to capture the trends of 10 years of longer time span.

IV. RESEARCH DESIGN

Rising prices of crude oil push inflation and adversely affect the gross domestic product of country. Crude oil is a key asset for risk hedging and Investment opportunity, hence investors are much fascinated in keeping account of forecasted prices. Forecasting of crude oil prices by using different methods may assist business operations, government policymakers and also to investors in commodity market. Keeping the interest of all stakeholders of crude oil in mind, this study predicts volatility in crude oil prices of Indian market using ARMA model. The monthly sample data of crude oil price (in INR per barrel) of last 23 years has been taken from the time period of January 1995 to May 2018. Data has been retrieved from the Indian government website of www.data.gov.in. Percentage change of crude oil prices is calculated by differentiating from previous month value. This change is signifying volatility in crude oil prices. Initially the different unit root tests are used to test that net change crude oil price series is stationary or non stationary. Box-Jenkins methodology has been used for developing a forecasting model of volatility in crude oil price in India. Different iterations are carried out to fetch the best suitable model for forecasting. Criterion of minimum Akaike Information Criteria (AIC) has been opted to arrive at fit good ARIMA model.

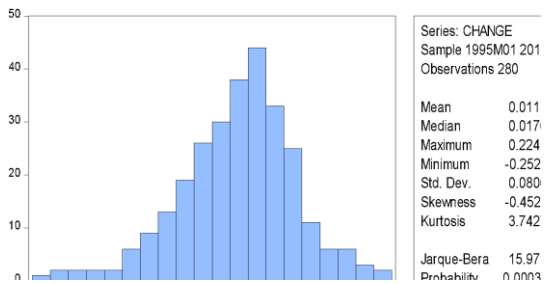
A Autoregressive Integrated Moving Average Model

The ARIMA as recommended by Box-Jenkins is a frequently used and stylish technique for the times series forecast. This technique is quite common in econometrics terminology for the times series analysis [18].

The general Box-Jenkins (ARIMA) model for y is written as:

$$y^* = \emptyset y_{t-1} + \emptyset y_{t-2} + \ldots + \emptyset y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q}$$

Figure 1: Descriptive Statistics



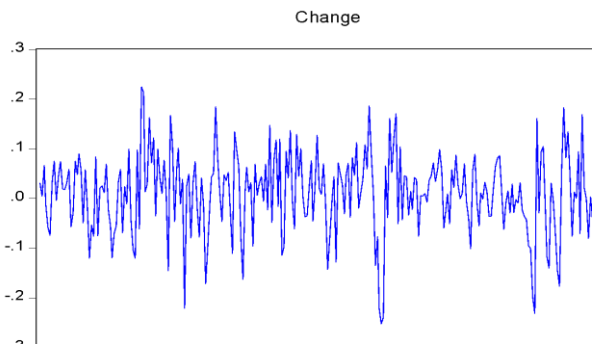
Source: Author's Compilation Using Eviews 10

Descriptive statics demonstrates that average variation in crude oil prices between the period of January 1995 to May, 2018 has remained 0.011307 or approximately 1% with standard deviation of 0.80628 or approximately 8% which shows the high instability in the crude oil price in Indian crude oil market. [20] suggested that in the case of normal distribution in the data series, the value of skewness should between -1 to +1. The value of Kurtosis must be within the range of -3 to +3. However, some other people use the limit of -2 to +2. In the present study skewness meet the necessary conditions of normality, but Kurtosis has value >3. Further, there is also a method which is most frequently used to check the normality in data series as advocated by [4] This technique is later derived by [16] as the Lagrangian Multiplier (LM) test and knows commonly known as JB statistics. JB test statistic is much greater than 5.99 (chi square table value at 2 degree of freedom). This indicates that there is lack of normality in data series and null hypothesis does not hold true.

A. Stationary Test

It is mandatory while using Box-Jenkins methodology that variable or data must be stationary. The data series or variables are said to be stationary if their means and variations for longer time horizon remain stagnant. To check whether crude oil data series is stationary or not, firstly line diagrams have been used for change in crude oil prices. Secondly, [8], [19] and [22] tests have been applied. First all the tests are applied at level without intercept and trend, with intercept and with intercept as well trend. If data series do not come stationary at level than these tests are applied at first difference or second difference.

Figure 2: Percentage change in crude oil prices January 1995 to May 2018



Source: Author's Compilation using Eviews 10

Line diagram is showing monthly change in crude oil prices (figure 2). It demonstrates that volatility in crude oil prices is not going to follow particular trend over the period of time. Overall trends indicate that data series for change in crude oil prices is stationary at level. This reflects that mean change in crude oil prices and variation in it throughout the study period is constant. This further indicates that data series of crude oil prices is stationary at level.

B.Unit Root Tests

This test is conducted by using three different techniques i.e., ADF, PP and KPSS [8], [19], [22] and by setting up null hypothesis that data series of crude oil price is not stationary and alternate hypothesis that data series of crude oil price is stationary. In the case of KPSS test acceptance of null hypothesis indicates (H0) that data series of change in crude oil is stationary. The rejection of null hypothesis or acceptance of alternate hypothesis means that (H1) that data series of change in crude oil is not stationary

Table 1: Consolidated unit root test

	ADF Test	PP	DF-GLS(ERS)	KPSS
	Level	Level	Level	

Without C and T	13.08958 * (0.0000)	13.1201 * (0.0000)	NA	NA
With C	13.2750* (0.0000)	13.2538 * (0.0000)	12.7916* (0.0000)	0.07075** 0.73900
With C and T	13.2611* (0.0000)	13.2361 * (0.0000)	13.1143* (0.0000)	0.03695** 0.21600

Note: * Significant at 1% level (Change is stationary)

**** At 1% level (Change is stationary)**

Table 1 portrays the values of different unit root test used in the present study. Associated statistics of all the tests (without C and T, with C and with C as well as C and T) except KPSS is much higher than 1.96 and p value < 0.01. In the case of KPSS data series is assumed to be stationary when null hypothesis is holds true. So in the case of KPSS, calculated value is much less than critical value at 1% level of significance (as shown parenthesis). So test statistics of all unit root tests demonstrate that volatility in crude oil prices is found stationary at level.

Table 2: Different Models with AIC, BIC and HQ values.

Model	AIC*	BIC	HQ
(4,3)(0,0)	-2.240825*	-2.12399*	-2.19396*
(4,4)(0,0)	-2.231061	-2.101247	-2.17899
(2,2)(0,0)	-2.229713	-2.15182	-2.19847
(1,0)(0,0)	-2.229712	-2.19076	-2.21409
(2,3)(0,0)	-2.228398	-2.137529	-2.19195
(0,2)(0,0)	-2.224967	-2.173041	-2.204140
(0,1)(0,0)	-2.224074	-2.185130	-2.208453
(2,0)(0,0)	-2.224067	-2.172141	-2.203239
(1,3)(0,0)	-2.223890	-2.146002	-2.192649
(1,1)(0,0)	-2.223625	-2.171699	-2.202798
(3,1)(0,0)	-2.222420	-2.144532	-2.191179
(3,4)(0,0)	-2.222242	-2.105410	-2.175381
(3,3)(0,0)	-2.221272	-2.117421	-2.179617
(1,4)(0,0)	-2.218473	-2.127603	-2.182026
(0,3)(0,0)	-2.218267	-2.153360	-2.192233
(3,0)(0,0)	-2.218162	-2.153255	-2.192128
(1,2)(0,0)	-2.218014	-2.153107	-2.191979
(3,2)(0,0)	-2.217270	-2.126420	-2.180822
(2,1)(0,0)	-2.217194	-2.152287	-2.191160
(4,0)(0,0)	-2.216205	-2.138316	-2.184964
(4,1)(0,0)	-2.2.21506	-2.124190	-2.178612
(0,4)(0,0)	-2.213501	-2.135613	-2.182260
(2,4)(0,0)	-2.209663	-2.105812	-2.168009
(4,2)(0,0)	-2.209021	-2.105170	-2.167366
(0,0)(0,0)	-2.18724	-2.161283	-2.176832

Source: Author's calculations using Eviews 10

Table 2 reports the model selection criteria, all the models have been shown as per the ascending value of AIC. The good fit ARIMA model has been obtained after carrying out several iterations and comparing the AIC value of different models. The most suitable model to predict the volatility in crude oil prices is ARIMA (4,3) (0.0) since it contains the minimum AIC. Table 2 shows the 25 models tried in the present study to investigate the best fit model of forecasting. As demonstrated in the given table that model (4, 3) (0,0) has lowest Akaike Information Criteria (AIC) i.e., -2.240825.

Table 3: Model Selection Criteria Table

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.011839	0.002636	4.49073	0.0000
AR(1)	-0.323488	0.050677	-6.383380	0.0000
AR(2)	0.700163	0.041577	16.84265	0.0000
AR(3)	0.794768	0.040097	19.82101	0.0000
AR(4)	-0.272967	0.048304	-5.651061	0.0000
MA(1)	0.559893	0.123973	0.045162	0.9640
MA(2)	-0.55989	20.51601	-0.027291	0.9782
MA(3)	-0.99999	57.93849	-0.017260	0.9862
SIGMASQ	0.005709	0.061893	0.092242	0.9266
R-square	0.220892	Akaike info criterion		-2.2408
Adj. R-square	0.206931	Schwarz criterion		-2.1239
S.E. of regression	0.076804	Hannan-Quinn criter.		-2.1939
Anova or F Value (P value)	4.559261 (0.0000)	Durbin-Watson stat		1.9993

Table 3 shows the summary of model chosen as per the criteria mentioned earlier. R square 0.220892 and adjusted R square is 0.206931 respectively. It means that in the current model (4,3) about 22% variance is explained by all the independent variables together. F statistics shows the significant value i.e., 4.559261 as p value (0.000064) of this statistics is > 0.01. According to [9] if DW ratio is two or near to two then there is no problem of autocorrelation. In the current model, this ratio is near to two. So there is no problem of autocorrelation or serial correlation. The different coefficients as shown of all significant variables i.e., AR (1) to AR (4) are recommended to be used to forecast the future change in crude oil prices (per barrel). Significant variables are only those variables whose t statistics is greater than 1.96 or whose p value < 0.05. MA (1) to MA (3) are not showing significant value in the proposed model.

Figure 3: Forecast Comparison Graph

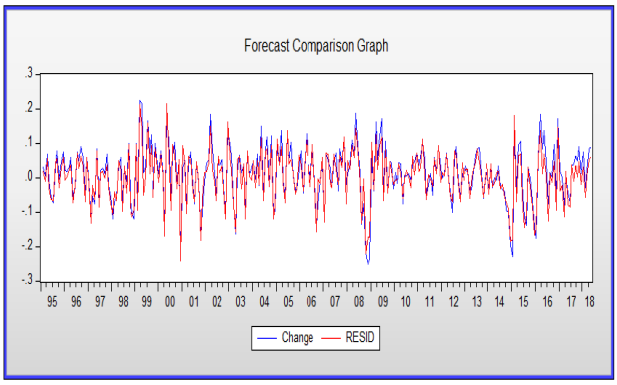


Figure 3 depicts the forecast comparison graph.

Figure clearly shows that residual as highlighted with red line has remained between -0.1 to 0.1 in maximum of period during last 23 years. In some of the period this error is higher and ranged -0.2 to 0.2. Specifically, for longer period the error or residual is less as compare to other period. Similarly, for the first two years residual value is less. So this model can be recommended for shorter period as well as very longer period of time.

Table 4: Evaluation Statistics

Model	RMSE	MAE	MAPE	Theil U1
(4,3)(0,0)	**0.027280**	**0.021763**	**108.0696**	**0.173942**

Source: Author's Calculations with Eviews10

The different performance measures viz., MSE, MAE, RMSE, MAPE and Theil's U-statistics have also been used to assess forecasting precision and for comparing the various time series models tried using ARIMA technique. MSE measures the absolute t of the model to the data, or in other words, how close the observed data points are to the model's predictions [5]. MAE calculates the absolute errors between the observed and the predicted value [5]. MSE gives more emphasis on the larger errors which leads to more conservative measurements than the MAE. RMSE equals to the square root of the MSE value and is represented on the same units as the response variable [26]. RMSE can be interpreted as the standard deviation of the unexplained variance. RMSE values (≥0.5 and 1.0, respectively) reflect the model's poor ability to accurately predict the model. Mean Absolute Percent Error (MAPE) is error above high and low values are not subjective by using the previous error metrics. MAPE measures the error relatively to the real values. In other words, MAPE is a method to check that how large or small is the differences between the forecasts [29]. Lower value (MSE, RMSE, MAE reflects good predictability of ARMA model (table 4).

V. CONCLUSION

The present paper forecast the volatility in crude oil price (per barrel) with the help autoregressive moving average method (ARMA). In order to develop good fit model and to predict instability in crude oil prices the monthly sample data of change in crude oil price (in INR per barrel) are taken from January 1995 to May 2018. The unit root tests have been used to test that the instability in crude oil price series is stationary or non stationary. It is observed that series were stationary at level. Different models have been tried to obtain best suitable model for forecasting. Results of the study states that ARIMA (4, 3) (0, 0) best suitable model to forecast the volatility in crude oil price in India. Model developed to predict volatility in future crude oil prices may be lucrative to all such parties who are keenly interested in crude oil. Specifically, forecasted volatility in prices may be useful to various authorities of centre state government of India (GOI) for deciding the future retail price of various petroleum products. Policymakers may be able to know the impact of forecasted volatility in crude prices on different economic variables. Business communities will be benefited by knowing in advance the future spot price of different petroleum products which may influence their business activities. The prime benefit for this community will be that uncertainties associated with crude oil price fluctuation will be neutralised, consequently they may be able design their business strategies accordingly. The coefficient of all significant variables may help investors of commodity market as they will be able to foresee the future prices.

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