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ANALYSIS OF THE DYNAMICS OF CRUDE OIL PRICES IN RELATION TO THE DOLLAR AND GOLD PRICES– INDIAN PERSPECTIVE.

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Abstract:
As one of the most essential energy sources in our nation, crude oil is also one of the most important Imported goods. India imports around 84% of its total Crude oil needs. This clearly illustrates the extent to which fluctuations in crude oil prices effect our economy. The energy industry is one of the most volatile industries, and energy dependence is substantial. Additionally, crude oil is a significant commodity traded on the commodities market. Considering all of the aforementioned variables, fluctuations in the price of crude oil have a significant influence on the nation's economy as a whole, making crude oil forecasting a necessity. This study analysed data from 2000 to 2021 to develop a very accurate predictive model. In addition to crude oil prices, macroeconomic indicators such as gold prices and dollar exchange rates have been collected and evaluated using ARIMA model.
Key words: Crude oil, Gold, Dollar, Fluctuation, prediction, ARIMA model.

Introduction:

Crude oil is one of the vital energy sources that serves as a gauge of a nation's economic health. India is reliant on crude oil imports for more than 80 percent of its crude oil requirements. In 2016, India imported over 84% of its crude oil and petroleum products. India purchased crude oil worth around US$77 billion or 239 million metric tonnes (MT) in 2020-21, representing more than 19 percent of the country's total imports. In 2019–20, about 85 percent of the demand for petroleum products was met by imports. Petroleum constituted twenty-five percent of India's total imports, with a gross import volume of around 270 MT valued at US$119 billion. This is a huge increase compared to 2006–07, when imports of around 145 MT accounted for over 77% of consumption.

Classification of Crude oil:

Throughout the world, oil is extracted. Brent Crude, West Texas Intermediate, and Dubai and Oman are the three primary crude oil sources that serve as standards for rating and pricing other oil suppliers.

Brent Crude is a blend of 15 unique North Sea oil sources situated between Scotland and Norway. The bulk of Europe receives oil from these sources. West Texas Intermediate (WTI) is a lighter

oil that is produced mostly in Texas, United States. It is of the finest quality and is "sweet" and "light." WTI supplies much of North America with crude oil.

Dubai crude, often popularly referred to as Fateh or Dubai-Oman crude, is a light, sour oil produced in Dubai, United Arab Emirates. Recent oil production has begun in the neighboring country of Oman. Oils from the Persian Gulf that are mostly exported to Asia are priced relative to Dubai and Oman crudes.

It is believed that the United States has the largest oil reserves, followed by Russia and Saudi Arabia. According to a 2016 survey, the numbers for the top 10 nations are presented in the table below.

Country	Estimated oil reserves (Billions of barrels)
United States	**264**
Russia	**256**
Saudi Arabia	**212**
Canada	**167**
Iran	**143**
Brazil	**120**
Iraq	**117**
Venezuela	**95**
Mexico	**72**
China	**59**

Recently, oil consumption in growing economies such as China and India has surged. This tendency is anticipated to continue, but at a slower rate (EIA, 2008). Over the last two decades, oil price fluctuations have undergone significant changes, including the introduction of new oil producers such as Canada, Alaska, and the North Sea. Moreover, the rise in oil prices has made certain oil wells commercially feasible. On the supply side, East Asian countries such as China, India, and Malaysia are expanding rapidly. China has surpassed the United States as the world's second biggest oil consumer, reflecting changes in the composition of the demand equation. New environmental restrictions have also promoted the use of light oil, which contains less Sulphur. These regulations have increased the strain on refinery utilisation. (2018) (Hamza & Alredany).

Recent emphasis has been focused on the volatility of crude oil prices, since crude oil is the most strategic and traded commodity on the planet. Oil-producing nations, oil firms, individual refineries, oil-importing nations, and speculators engage in international crude oil trading. (2015) (Bildirici & Ersin). Although the price of crude oil is mostly driven by supply and demand (Hagen 1994; Stevens 1995), it is also affected by a number of irregular occurrences, including stock levels, economic growth, political considerations, political instability, OPEC actions, and traders' psychological expectations (Yu et al. 2008). It is well acknowledged that oil price volatility has a substantial influence on economic activity. Commodity market prices change in lockstep with the rise and fall of the oil price, therefore any dramatic spike or reduction in oil prices causes an economic slowdown and price variations for other commodities. Consequently, projecting crude oil prices is a crucial field of study, and modeling/forecasting oil prices is hampered by intrinsic challenges such as excessive volatility (Wang et al. 2005).

Due to the fact that crude oil spot prices are often seen as a nonlinear and nonstationary time series that is impacted by a number of variables, it is rather challenging to properly anticipate crude oil prices (Yu et al. 2008). While oil prices may not always react instantly to fresh information, limited liquidity and infrequent trading on imperfect markets may result in a delay (McMillan and Speight 2006; Monoyios and Sarno 2002; Lee et al. 2008). When big worldwide political and economic events occur, such as changes in government policies, geopolitical dangers, investor attitude, and natural catastrophes, structural changes in oil prices and, subsequently, panic indexes adopt a nonlinear connection. 2019 (Lin, Liang, & Tsai).

The conditional variance of oil returns demonstrates time-varying volatility. The evidence for unequal effects in conditional variance is contradictory. There is no indication of risk-reward trade-offs. There is evidence that the conditional standard deviation is a more accurate estimate of the volatility of oil returns than the conventional conditional variance. (2010) (Mohammadi & Su). Numerous economists, practitioners, and analysts are intrigued by the current fluctuations in the stock market; they strive to understand the fundamental reasons of these huge swings, which cost the economy roughly billions of dollars. The key factors of the stock market are the interest rate, currency exchange rate, and oil prices in particular. (Ahmed, n.d.)

Crude Oil Import Scenario of India:

- In December 2021, the average daily crude oil imports into India were 4,243.758 barrels. In December 2020, the previous peak of 4,033,050 Barrel/Day was attained.
- From December 1980 to 2021, annual data on India's crude oil imports indicate an average of 1,557.335 Barrel/Day.

- In 2018, the statistics reached an all-time high of 4,543.634 Barrel/Day and an all-time low of 278.073 Barrel/Day.

Eighty-four percent of India's crude oil requirements are covered by imports, and this proportion has continuously increased over time. Too great is the disparity between domestic demand and output. The majority of India's oil imports originate from Iraq and Saudi Arabia in the Middle East. India Imports Crude oil from various parts of the world, they are:

- Middle East – 52.7%
- Africa – 15 %
- United States of America - 14%

Research gap:

After analysing prior research, it is clear that changes in economic indicators have a major influence on crude oil prices. Numerous financial time series have leptokurtic distributions, large tails, and nonlinear conditional volatility. This trait reduces the predictive power of traditional models like the ARCH and GARCH models (Bildirici, Melike).

A little amount of research has been undertaken to demonstrate the similar association between the Indian crude oil basket price and the price of crude oil. Insignificant research has also been conducted to determine the worldwide elements driving fluctuations in the Indian basket crude oil price. In other words, the Indian basket crude oil price benchmark has garnered minimal attention, similar to other international crude oil price benchmarks. This research aims to discover the elements that cause fluctuations in the price of Indian basket crude oil. As a consequence, it contributes originality to this area of study. Crude oil prices are sensitive to changes in other significant macroeconomic indices, such as the gold price, the US dollar to Indian rupee exchange rate, the Gross Domestic Product, the SENSEX, and the NIFTY. This study employs Univariate analysis to examine the relationship between significant macroeconomic indicators and crude oil prices over the medium and long term. Which in turn aids the research in determining the feasibility of crude oil price predictions after accounting for the impact of economic factors on the commodity.

Statement of Problem:

Revenue and expenditures are the lifeblood of every economy, and they may be brought in via several means. Income is often broken down into two categories: taxable and nontaxable. Forex, gold prices, stock market indexes, GDP, and crude oil prices are all examples of macroeconomic factors that affect the economy. These metrics show a statistically significant positive correlation. To help reduce price volatility in the future, this research builds univariate and multivariate models to predict crude oil prices and aims to establish a linear link between these factors.

Businesses that depend on crude oil, commodities speculators, and investors may all benefit from accurate price predictions due to crude oil price forecasting. The availability of crude oil is essential to the prosperity of every country. All of the country's macroeconomic indices are

affected to some degree by it. The results of this research will help us estimate the long-term and short-term consequences of rising crude oil prices on key economic variables including the US dollar/gold exchange rate.

Objectives of the study:

a) To analyse the impact of Macro Economic Indicators on Crude oil Price
b) To forecast the Crude oil prices by considering Macro economic indicators.
c) To interpret the forecasted price of Crude oil.

To draw the significance and to forecast crude oil price this study has adopted predictive analysis. The data has been first tested for Multiple Linear regression which runs on mean difference has high Multicolinearity within the variables hence further Quantile regression test has been tested. This study for analysis and prediction purpose has considered Crude oil as dependent variable and Macro Economic indicators such as Forex (US $), Gold Price, Sensex, Nifty as these Indicators will have high impact on Crude oil prices.

Initially study has considered Descriptive Statistics and Correlation to check linear relationship among the variables.

Descriptive Statistics:

	Crude	Dollar	Gold
count	252.000000	252.000000	252.000000
mean	63.224118	54.157738	1870.536997
std	28.870070	10.678496	1133.994996
min	18.240000	39.195000	386.299579
25%	40.587875	45.643750	663.840979
50%	60.443794	48.690000	1989.640592
75%	78.345516	64.486250	2718.265889
max	132.471248	75.590000	4726.129845

Correlation:

	Crude	Dollar	Gold
Crude	1.000000	0.190393	0.429275

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.2931	0.025	11.570	0.000	0.243	0.343
Dollar	-0.4844	0.091	-5.305	0.000	-0.664	-0.304
Gold	0.8790	0.101	8.703	0.000	0.680	1.078

	Crude	Dollar	Gold
Dollar	0.190393	1.000000	0.841202
Gold	0.429275	0.841202	1.000000

After looking at the correlation matrix study understands positive relationship between the Dependent and Independent variables. Further study gives ample opportunity to go for predictive analysis.

The twenty-one years data has been divided into Sample data set and Forecasting data set to have a better prediction model.

Initially the data has been tested for Linear Regression with Crude oil as dependent variable and Dollar price as independent variable which gave a very less prediction factor to the data hence the study has added Gold also to the Regression equation. The equation to calculate Multiple Linear Regression in this case will be:

$\alpha + \beta_1 x_1 + \beta_2 x_2$

Hypothesis:

H_0: There is no significant Linear relationship between Crude oil, Dollar and Gold Prices

OLS, using observations 2000:04-2020:03 (T = 240)

Dependent variable: Crude Oil Price

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
Constant	95.8684	9.88655	9.697	<0.0001	***
Dollar	−1.54591	0.240360	−6.432	<0.0001	***
Gold	0.0288687	0.00235026	12.28	<0.0001	***

Mean dependent var	64.15792		S.D. dependent var	29.15433

Sum squared resid	114254.3		S.E. of regression	21.95645
R-squared	0.437570		Adjusted R-squared	0.432824
F(2, 237)	92.19286		P-value(F)	2.42e-30
Log-likelihood	−1080.410		Akaike criterion	2166.821
Schwarz criterion	2177.263		Hannan-Quinn	2171.028
rho	0.967235		Durbin-Watson	0.099877

The regression equation from the above table is **95.8684 – 1.54591x$_1$ + 0.0288687x$_2$** and later Variance inflation Factor has been tested for Multicollinearity problem and model doesn't have Multicollinearity problem and p-value is less than 0.05 hence study rejects null hypothesis and accepts alternate hypothesis that is there is a significant relationship between Crude oil, Dollar and Gold Prices.

ARIMA model with Seasonal Lags has been considered to test the model. Dollar as Independent and Crude oil as Dependent variable ARIMA model has been tested.

AR – 1, I – 1, MA – 1 (seasonal) has been considered with 1 lag points for analysis purpose. The equation being; $\hat{y}t = \mu + \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} - \theta_1 e_{t-1} - \ldots - \theta_q e_{t-q}$

ARIMA, using observations 2001:04-2020:03 (T = 228)
Dependent variable: (1-Ls) Crude Oil Price
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
Phi_1	0.781494	0.0553394	14.12	<0.0001	***
Theta_1	−1.00000	0.0451871	−22.13	<0.0001	***
Dollar	1.19674	0.303861	3.938	<0.0001	***

Mean dependent var	1.776930		S.D. dependent var	22.94899
Mean of innovations	2.743051		S.D. of innovations	20.84486
R-squared	0.539924		Adjusted R-squared	0.535834
Log-likelihood	−1023.197		Akaike criterion	2054.394
Schwarz criterion	2068.112		Hannan-Quinn	2059.929

		Real	*Imaginary*	*Modulus*	*Frequency*
AR (seasonal)					
	Root 1	1.2796	0.0000	1.2796	0.0000
MA (seasonal)					
	Root 1	1.0000	0.0000	1.0000	0.0000

The model equation may be derived from the data in the previous table as follows:

$\hat{y}t = 1.19674 - 1\ yt_{t-1} - 0.781494\ e_{t-1}$

The p-value indicates that the model has a substantial effect on prediction. The value of the dollar is a reliable indicator of the cost of crude oil. The research will also examine the relationship between Gold and the predicted price of crude oil.

ARIMA, using observations 2001:04-2020:03 (T = 228)
Dependent variable: (1-Ls) Crude Oil Price
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
Phi_1	0.628949	0.0681103	9.234	<0.0001	***
Theta_1	−1.00000	0.0576984	−17.33	<0.0001	***
Gold	0.0114775	0.00286535	4.006	<0.0001	***

Mean dependent var	1.776930		S.D. dependent var	22.94899
Mean of innovations	3.241575		S.D. of innovations	20.81682
R-squared	0.507293		Adjusted R-squared	0.502914
Log-likelihood	−1025.709		Akaike criterion	2059.419
Schwarz criterion	2073.136		Hannan-Quinn	2064.953

		Real	*Imaginary*	*Modulus*	*Frequency*
AR (seasonal)					
	Root 1	1.5900	0.0000	1.5900	0.0000
MA (seasonal)					
	Root 1	1.0000	0.0000	1.0000	0.0000

From the table he ARIMA equation can be drawn as follows.

$\hat{y}t = 1.19674 - 1\ yt_{t-1} - 0.781494\ e_{t-1.}$

p-value of the above table also helps the study to understand that the model has strong predictable capacity with all the variables having p-value less than 0.05.

Hence the study understands that ARIMA is one of the univariate model which has the strong predictable capacity of Crude oil against its relationship with Dollar and Gold prices.

Interpretation from the above analysis:

- In the above study Crude oil has been considered as a Dependent variable, Dollar and Gold prices as Independent Variable.
- Initially Correlation of Crude oil with Dollar and Gold prices has been established and study understood that there is a positive relationship among the variables.
- Further Multiple Linear regression has been drawn to establish Linear relationship among the variables. With no Multicollinearity study established strong relationship among Dependent and Independent Variables.
- To establish prediction of Crude oil when compared with Dollar and Gold prices study has used ARIMA model which showed a strong predicting capacity of the model.

Conclusion:

About 82% of the crude oil used in our country is imported. Which contributes substantively to the study's ability to comprehend the impact of Crude oil Prices on the State of the Economy as a Whole. Therefore, an accurate forecast of future crude oil prices is a must for the nation.

The ability of the ARIMA model to forecast Gold and Dollar prices relative to Crude oil prices was tested using a Univariate test in this research. Insights gained from this study not only led to the realisation that ARIMA is a promising candidate for predicting future crude oil prices but also convinced the researchers that other methods, such as Univariate and Multivariate analysis, have promise as well.

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