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Evolution of Crude Oil Prices during the COVID-19 Pandemic: Application of Time Series ARIMA Forecasting Model

Assia ATIL [1], Bouchra MAHFOUD [2]
1 PhD Student, Department of Economics, LADBG, Université 8 Mai 1945- Guelma, Algeria
2 PhD Student, Department of Economics, LRIEDD, Badji Mokhtar- Annaba University, Algeria

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Abstract

Given the high level of uncertainty experienced by open economies in the light of Coronavirus pandemic (COVID-19) and global economic recession expectations, predictive studies become extremely important, particularly when it comes to commodities with high global demand. Because crude oil is a major source of energy on which most economic and commercial activities are based, the primary aim of the study is to forecast oil prices for the within and out-of-sample period using the Autoregressive Integrated Moving Average model (ARIMA). Study results showed that the ARIMA model is delivering satisfactory results in the prediction process. Moreover, prices are expected to see a slight increase and stability over the next few months.

1. Introduction

Economic activity is slowing as concerns about the how an economy can retreat are growing. Economic and financial crises lead to increased uncertainty, decreased demand, which leads the global economy to recession. Because of the Coronavirus (COVID-19) outbreak, the world is currently experiencing a hard state of uncertainty; social distancing policies and quarantine restrictions have disrupted economic and commercial activities. In addition, Coronavirus caused an increase in unemployment rates across many countries, including developed: The US unemployment rate has risen to 14.7%, with 20.5 million jobs lost this April (BBC, 2020). Despite being an epidemiological phenomenon, the Corona pandemic has serious repercussions on the global economy, including oil prices that have experienced a significant decline since the onset of the pandemic. In this regard, this paper is concerned with a predictive study of crude oil prices for the within and out-of-sample for three months until August 24, 2020, using the Autoregressive Integrated Moving Average (ARIMA) to answer the following main question:

How does the ARIMA model forecast crude oil prices to be in the next three months?

This main question stimulates the following sub-questions:

- Why do global economic and political problems affect oil prices?
- How does COVID-19 impact the economy?

Study Hypotheses:

In order to understand this study and answer these questions, we base the study on the hypothesis that the ARIMA model can provide satisfactory results in forecasting oil prices.

Study Objectives:

This study aims to define the importance of crude oil in the economic life and its link with the prevailing global conditions, in addition to giving a comprehensive and quick look at the Coronavirus and some of its effects on the global economy. On the other hand, this predictive research aims primarily to provide a future view about oil prices up to August 24,2020, though this remains a relative issue and closely relate to potential virus trends.

Study Importance:

This study derived its importance from the importance of the recent conditions characterized by uncertainty, from the COVID-19 outbreak that has spread all over the world and caused significant losses. Furthermore, crude oil is a very critical source of energy in the world as a whole. Both nations, whether exporting or importing, are concerned with price changes (Kosakowski, 2020).

2. Literature Review

Changes in oil prices are subject to several overlapping and intertwining factors, including what is economic, and related to the supply and demand mechanism and interaction between them. As the size of the global oil supply is affected by the productive capacity and distribution of production quotas between global producers both inside and outside OPEC (Kosakowski, 2020).

Prices are also influenced by geopolitical changes at the global and regional level in oil-producing countries and some major oil-consuming countries. The occurrence of any kind of political turmoil (such as war outbreak , rebellion, riots, revolution, and coup) that threatens production, transport, and distribution routes or places of consumption, affecting the volume of production, the quantity of global supply, the level of demand, and thus the level of oil prices for short-term. For example, in July 2008, the price of a barrel of oil was $128 because of instability and consumer fear of war in Afghanistan and Iraq (Ganti, 2020).

Besides, many other factors could be described as behavioral, and cause oil price fluctuations as they are related to the behavior of customers and financial investors in the decision to buy or sell oil and gas contracts. These depend on trust, expectations, speculation, and the desire to achieve earnings. Such decisions are also affected by geopolitical circumstances and assumptions about the course of price change, up or down (Quan, 2014).

Interest rates could influence oil prices. One of the basic theories argued that interest rates raise the cost of consumption and suppliers, thereby decreasing the amount of time and energy people spend driving. Fewer drivers on the road equate to lower oil demand, which may lead to lower oil prices. That relation is considered as a reverse relation in this situation. In the same idea, as interest rates decline, customers and businesses can borrow and spend money more freely, thus growing oil demand. The further oil that OPEC places on output rates, the more customers pay the price (Lioudis, 2020).

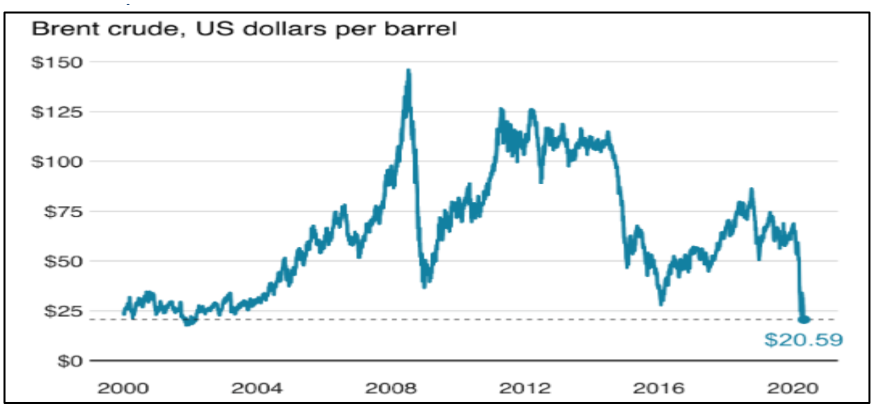
For these reasons, fluctuations in world oil prices influence, directly or indirectly, other goods. Oil prices thus reflect the global economic situation because of their close ties to economic growth. Low oil prices are typically an indicator of a general economic slowdown due to a decline in overall production and a rise in high total demand. As such, oil price moves can trigger inflation or deflation, causing global economic crises.

Energy producers and customers periodically estimate oil price and other commodities over a span of 20 or 30 years for assessing both strategic and investment decisions (Robert S. Pindyck, 1999).

Being a big manufacturing country, China is one of the rising oil consumers in the world. Fluctuations in oil price influenced several aspects of China's economic development. In this regard, Li Quan conducted a predictive analysis of Daqing crude oil prices for the first 10 months of 2011 using the ARIMA model, based on data on the monthly average price of Daqing crude oil from January 2000 to December 2010.

With the emergence of COVID-19 and its pervasive and quick dissemination across and within countries, lifestyles have changed unprecedentedly. The precautionary measures introduced by governments, in particular, the implementation of social distancing and confinement measures to disrupt contagion have had a significant effect on different human activities and social interactions, as digitization has eroded the means of direct contact between individuals. The fact is that such an abrupt transition did not only impact the social relationship, but affected domestic economic stability, and the global economic development process as a whole. It is worth noting that the extent of the effects varied from country to country and from region to region. If China, the first epicenter of the disease, was able to contain the disease, as did Japan and Singapore, then several other nations, particularly the Europeans, and the United States of America, showed their inability to prevent the rapid spread of the virus. "Live at home" made the economic impacts of the COVID-19 greater than expected. After the oil prices recovering after the oil crisis for the year 2014. Corona crisis came to cause a similar collapse in prices:

Fig. 1. Crude Oil Prices Downturn Caused by COVID-19



Source: Bloomberg. April 27, 2020. 7 GMT (from BBC web site)

Since the beginning of the COVID-19 outbreak in China at the end of 2019, oil prices have been affected. Given China's position as the world's largest oil consumer, and the rapid spread of the virus across the world in Europe and the United States of America. The severe collapse in crude oil prices has reached $20, as shown in the line graph above, while US crude reached negative values.

Since the outbreak of the covid 19, several studies are appeared to explain the impact of covid 19 on oil prices fluctuations, Aloui et.al (2020) studid the impact of COVID-19 shocks on the energy futures markets, particularly on crude oil and natural gas S&P GS Indexes. By using the structural VAR model and stochastic volatility (TVP-SVAR model). The results showed that energy commodities S&P GS Indexes respond to COVID-19 shock that varying over time due to fundamentals factors as well as behavioral and psychological factors.

Nyga-Łukaszewska and Aruga (2020), investigated the impact of the COVID-19 cases on the crude oil and natural gas markets by using the Auto-Regressive Distributive Lag (ARDL) of the US and Japanese COVID-19 cases and energy prices from 21

January 2020 to 2 June 2020. They found e COVID-19 pandemic had a statistically negative impact on the crude oil price while it positively affected the gas pricein US, whereas the negative impact was only apparent in the crude oil market with a two-day lag (Nyga-Łukaszewska & Aruga, 2020).

In the same line of work, Prabheesh et.al (2020) focused on studying the relationship between stock price returns and oil price returns covering the COVID-19 period for major net oil-importing Asian countries, by fitting a DCC-GARCH model on daily data. The findings indicated a positive co-movement between oil price returns and stock price returns during the COVID-19 period. This indicates that falling oil prices act as a negative signal for the stock market.

3. Methods and Materials

Forecasting can generally be defined as a process that allows one to know the future values of an unknown and uncertain phenomenon often, not necessarily, a future event (Zarnowitz, 2020). Economists are very interested in forecasting to make the best decisions and appropriate policy choices. New methods of statistical inference have contributed a great deal to the development of current economic forecasting techniques, which have attracted the attention of those interested in social and economic data since they were first applied in the physical and biological sciences (Zarnowitz, 2020).

The predictive process, however, cannot be considered entirely reliable, even when quantitative methods are used. Changes sometimes occur which are not taken into account, as occurred during the subprime mortgage crisis (2007) when real estate prices fell, contrary to prevailing expectations.

3.1. Mathematical Models of ARMA Time Series

The forecasting process can be done through several types and methods. Time series analysis is one of the most used methods. We choose the Autoregressive Integrated Moving Average model (ARIMA) or what is also called the Box-Jenkins modeling, which is a time between the linear models commonly used in statistical methods. In order to predict future crude oil prices.

The basic idea behind the Box-Jenkins (BJ) forecasting methodology is to analyze the probability or random characteristics of the economic time series itself. Unlike traditional regression models, in which K interprets the dependent variable Y_t from the explanatory variables$(X_1, X_2, X_3,\ldots,X_k)$. BJ time series models allow the interpretation ofY_t by the past or slow (lagged) values of Y_t itself, and the current and lagged values of e_t , which are an unrelated random error term with zero mean and constant variance. That is, the limit for the white noise error.

- **The Autoregressive (AR) Model**

The equation below takes the following form:

$$Y_t = \mathrm{B}_0 + \mathrm{B}_1\mathrm{Y}_{t-1} + \mathrm{B}_2\mathrm{Y}_{t-2} + \cdots. + \mathrm{B}_p\mathrm{Y}_{t-p} + \mathrm{e_t} \;\ldots..(1)$$

$\mathrm{e_t}$: is the error term

The equation (1) represents the autoregressive model (AR) , when "p" is called the order. The value of p is determined experimentally using some criteria, such as the Akaike Information Criteria (AIC) (Gujarati, 2011).

- **The Moving Average (MA) Model**

Y_t can also be designed as follows:

$$Y_t = C_0 + C_1e_t + C_2e_{t-1} + \ldots. + C_1e_{t-q} \;\ldots..(2)$$

We express Y_t as the weighted or Moving Average (MA) of the current and past error limits for White noise. Model (2) is defined as the MA (q) model, and the value of q is also determined experimentally (Gujarati, 2011).

- **The Autoregressive Moving Average (ARMA) Model**

This type of models is a combination of two processes, Autoregressive process and Moving Average process, which is called a Autoregressive Moving Average process of mixed p and q respectively, and we write it as ARMA (p, q). We write its equation as in the following form (Gujarati, 2011) :

$$Y_t = B_0 + B_1Y_{t-1} + B_2Y_{t-2} + \cdots . + B_pY_{t-p} + e_t + C_0 + C_1e_t + C_2e_{t-1} + \dots . + C_1e_{t-q} \dots \dots (3)$$

- **The Autoregressive Integrated Moving Average (ARIMA)**

The BJ methodology is based on the assumption that the time series is stable or can be made stable by taking differences one or more times. This is known as the ARIMA model (p, d, q), where (d) indicates the number of times the time series differences should be taken to make it stable (In most cases d = 1). If a time series is already stable, we take only ARMA model (p, q) (Gujarati, 2011).

4. Results and Discussion:

The data that we are studying and analyzing are the weekly closing for the working days of Crude Oil Jul 20 in US Dollars (CL = F) during the period from 01/28/2013 to 05/18/2020. The sample size of 382 views, obtained from finance.yahoo.com/. We used the statistical program Eviews to carry out the study applied.

4.1. Data Description

Before creating a basic model that explains the phenomena studied, a general understanding of time series data is needed:

Table 1. Descriptive Statistics of Crude Oil Price Series in US Dollar

	Price
Mean	63.31453
Median	56.52000
Maximum	110.5300
Minimum	16.67000
Std. Dev.	22.05149
Observations	382

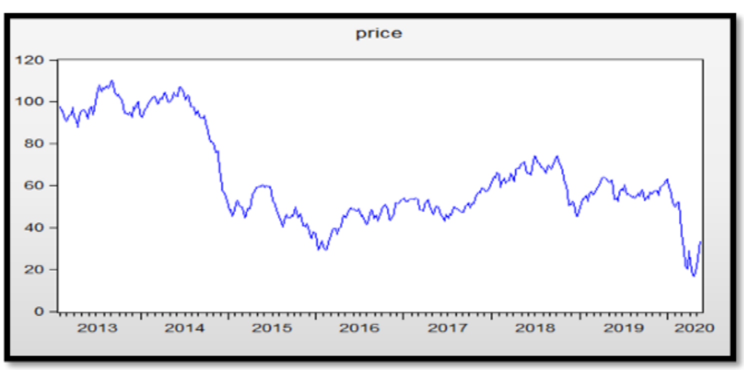
Source : Eviews Outputs

The table 1 above shows that the maximum price of crude oil recorded during the study period with a value of 110.5300 was on 02/02/2013 and the minimum price with a value of 16.67000 was on 04/20/2020. The table, also, shows the value of the mean, median and deviation, as they respectively reached 63.31453, 56.52000 and 22.05149.

4.2. Time Series Stability Test

Stability analysis of the time series is a necessary condition in the modeling process. We consider that crude oil price series is stable if its arithmetic average, variance, and covariance over time are constant. We can find out, however, that the series is unstable by graphically representing it:

Fig.2. Crude Oil Jul 20 (CL = F) graphical representation



Source: Eviews Outputs

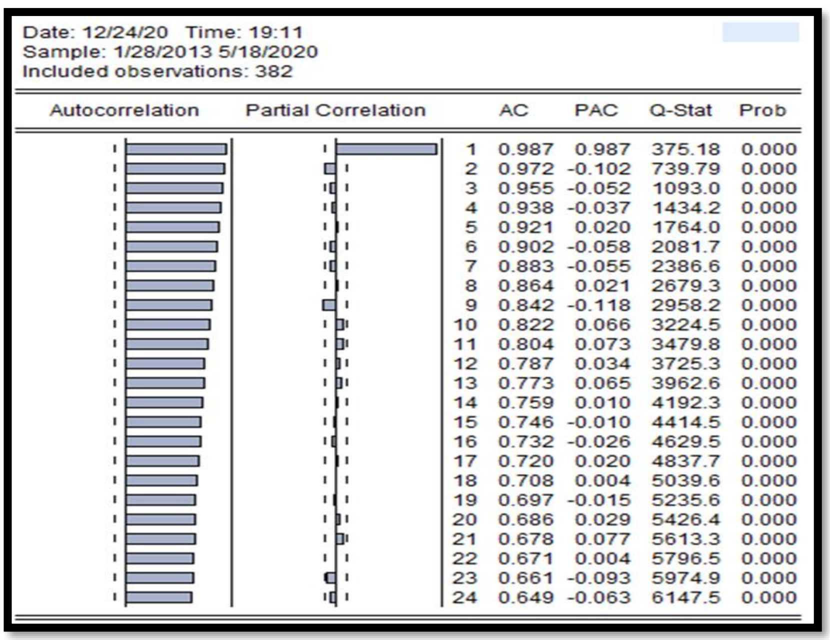
Figure (2) shows that the crude oil price series seems to be unstable because the moving average is unstable over time. By the autocorrelation function (ARF), we find that all parameters are above the confidence limits (outside the dashed small lines), it is slowly decreasing, which means the series are unstable. To verify that results, we use Augmented Dicky-Fuller Test's (ADF) stability test, where null hypothesis (H0) states the presence of unit root (the series is unstable). To ensure this, a Correlogram function was drawn for this series using Eviews:

Table 3. Unit Root Test Results on Crude Oil series at the 5%

Variable	**Augmented Dicky-Fuller (ADF)**					
	At level			**1st difference**		
Crude Oil	**t- statistic**	**Critical-value**	**prob**	**t- statistic**	**Critical-value**	**prob**
	-1.441371	-2.868928	0.5623	-16.63166	-2.868928	0.0000

Source: Eviews Outputs

Table 2. ARF and PARF at level



Date: 12/24/20 Time: 19:11
Sample: 1/28/2013 5/18/2020
Included observations: 382

	AC	PAC	Q-Stat	Prob
1	0.987	0.987	375.18	0.000
2	0.972	-0.102	739.79	0.000
3	0.955	-0.052	1093.0	0.000
4	0.938	-0.037	1434.2	0.000
5	0.921	0.020	1764.0	0.000
6	0.902	-0.058	2081.7	0.000
7	0.883	-0.055	2386.6	0.000
8	0.864	0.021	2679.3	0.000
9	0.842	-0.118	2958.2	0.000
10	0.822	0.066	3224.5	0.000
11	0.804	0.073	3479.8	0.000
12	0.787	0.034	3725.3	0.000
13	0.773	0.065	3962.6	0.000
14	0.759	0.010	4192.3	0.000
15	0.746	-0.010	4414.5	0.000
16	0.732	-0.026	4629.5	0.000
17	0.720	0.020	4837.7	0.000
18	0.708	0.004	5039.6	0.000
19	0.697	-0.015	5235.6	0.000
20	0.686	0.029	5426.4	0.000
21	0.678	0.077	5613.3	0.000
22	0.671	0.004	5796.5	0.000
23	0.661	-0.093	5974.9	0.000
24	0.649	-0.063	6147.5	0.000

Source : Eviews outputs

From Table (3) we note that the calculated ADF test statistics in absolute value are absolutely lower than the critical value in absolute value at the significance level of 5 percent. This is verified by the probability value (p-value) which is absolutely higher than 0.05. so we accept null hypothesis H0. But after taking the first difference, the series became stable where the statistic calculated at the absolute value of 16.63166 became completely greater than the critical value at the absolute value of 2.868928. We also dismiss the hypothesis H0 since the likelihood value (p-value) is totally less than 0.05 The crude oil price series is stable after first difference has been made. The analysis reveals this in the Correlogram: In order to estimate forecasting model quickly and efficiently, the Automatic ARIMA model can be used to select the best (AR) and (MA) automatically, without resorting to autocorrelation and partial autocorrelation, where the ranks (AR) and (MA) are determined by the lowest value of the (AIC) standard. Table (5) shows the appropriate rank:

From the table (5) above, we find that the best selected ARIMA rank is (1,1,0) where: the degree of Autocorrelation AR (p) is calculated to be AR=1; the degree of moving averages MA (q) is equal to MA = 0; as for 1 it is the degree of integration of the sequence. To confirm, a table has been inserted for the values of (AIC) until it has been confirmed that the lowest value for it is at rank (1.1.0). Table (6) shows that the lowest value for AIC is 4.757536 at the grade (1.0), the appropriate model for the study is ARIMA (1, 1.0).

After determining the degree of integration, we can determine both the Autoregressive Rank (AR) and the Moving Average (MA) rank by using Eviews.

Table 4. ACF and PACF after taking the first difference

Date: 12/24/20 Time: 20:48
Sample: 1/28/2013 5/18/2020
Included observations: 381

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.155	0.155	9.2132	0.002
		2	0.024	0.000	9.4389	0.009
		3	0.028	0.024	9.7317	0.021
		4	-0.033	-0.042	10.165	0.038
		5	0.067	0.080	11.906	0.036
		6	0.136	0.117	19.153	0.004
		7	0.016	-0.023	19.248	0.007
		8	0.053	0.048	20.334	0.009
		9	-0.039	-0.057	20.920	0.013
		10	-0.039	-0.019	21.505	0.018
		11	-0.030	-0.041	21.855	0.026
		12	-0.076	-0.078	24.162	0.019
		13	-0.021	-0.005	24.343	0.028
		14	-0.028	-0.033	24.655	0.038
		15	-0.034	-0.008	25.117	0.048
		16	-0.001	0.009	25.118	0.068
		17	-0.007	0.015	25.139	0.092
		18	-0.044	-0.025	25.909	0.102
		19	-0.085	-0.075	28.795	0.069
		20	-0.067	-0.030	30.584	0.061
		21	-0.083	-0.074	33.408	0.042
		22	0.049	0.073	34.376	0.045
		23	0.089	0.071	37.599	0.028
		24	-0.012	-0.030	37.656	0.038

Source: Eviews Outputs

Table 5. Automatic ARIMA Model Estimation Choice

Automatic ARIMA Forecasting
Selected dependent variable: DPRICE
Date: 05/22/20 Time: 20:29
Sample: 1/28/2013 5/18/2020
Included observations: 381
Forecast length: 0

Number of estimated ARMA models: 9
Number of non-converged estimations: 0
Selected ARMA model: (1,0)(0,0)
AIC value: 4.75753637506

Source: Eviews outputs

Table 6. AIC Values at Various Ranks

Model Selection Criteria Table
Dependent Variable: DPRICE
Date: 05/22/20 Time: 21:22
Sample: 1/28/2013 5/18/2020
Included observations: 381

Model	LogL	AIC*	BIC	HQ
(1,0)(0,0)	-905.689448	4.757536	4.788521	4.769829
(0,1)(0,0)	-905.754148	4.757875	4.788860	4.770168
(1,1)(0,0)	-905.689226	4.762771	4.804084	4.779161
(2,0)(0,0)	-905.689309	4.762771	4.804085	4.779161
(0,2)(0,0)	-905.721449	4.762940	4.804253	4.779329
(1,2)(0,0)	-905.333836	4.766146	4.817787	4.786633
(2,1)(0,0)	-905.439355	4.766698	4.818340	4.787186
(2,2)(0,0)	-905.167899	4.770513	4.832483	4.795098
(0,0)(0,0)	-910.222546	4.776034	4.796691	4.784229

Source : Eviews Outputs

Table 7. ARIMA (1,1,0) Model Results

Dependent Variable: D(PRICE)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 05/22/20 Time: 21:44
Sample: 2/04/2013 5/18/2020
Included observations: 381
Convergence achieved after 6 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.157152	0.046188	3.402413	0.0007
SIGMASQ	6.815842	0.380705	17.90320	0.0000

R-squared	0.020727	Mean dependent var	-0.167664
Adjusted R-squared	0.018143	S.D. dependent var	2.641669
S.E. of regression	2.617596	Akaike info criterion	4.767691
Sum squared resid	2596.836	Schwarz criterion	4.788388
Log likelihood	-906.2451	Hannan-Quinn criter.	4.775903
Durbin-Watson stat	1.996533		

Inverted AR Roots .16

Source : Eviews Outputs

Through the results obtained from Table (7), we observe that all parameters are statistically significant, that is, they differ significantly from zero at the level of 0.05.

4.3. Diagnostic Checking

Once the appropriate model for the Crude Oil Price series has been determined, it must be ascertained that the Residuals series has a White Noise.

According to Table (8) above, It can be shown that most of the coefficients of the residual series (et)'s partial and autocorrelation function are not significant and equal to 0 at the significance level 0.05. This can be verified by the use of the Ljung-Box test. The findings of this study showed that the normal residuals have a white noise, With regard to the fact that the Q-Stat value of this check is entirely smaller than the expected distribution value of χ^2 at various degrees of freedom and 5 percent at sense point.

Table 8. Residuals ACF and PACF

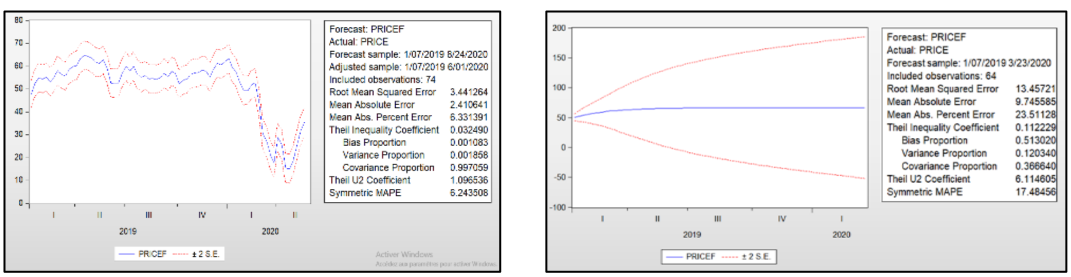
Date: 05/22/20 Time: 22:06
Sample: 1/28/2013 5/18/2020
Included observations: 381
Q-statistic probabilities adjusted for 1 ARMA term

	AC	PAC	Q-Stat	Prob
1	-0.003	-0.003	0.0045	
2	-0.004	-0.004	0.0109	0.917
3	0.033	0.033	0.4432	0.801
4	-0.040	-0.040	1.0701	0.784
5	0.041	0.041	1.7248	0.786
6	0.128	0.127	8.1114	0.150
7	-0.009	-0.006	8.1456	0.228
8	0.066	0.063	9.8387	0.198
9	-0.036	-0.042	10.357	0.241
10	-0.038	-0.029	10.920	0.281
11	-0.017	-0.034	11.035	0.355
12	-0.076	-0.087	13.298	0.274
13	-0.002	-0.008	13.300	0.348
14	-0.019	-0.036	13.445	0.414
15	-0.035	-0.020	13.945	0.454
16	0.008	0.009	13.970	0.528
17	-0.002	0.017	13.972	0.601
18	-0.038	-0.014	14.564	0.627
19	-0.067	-0.068	16.350	0.568
20	-0.047	-0.033	17.261	0.572
21	-0.078	-0.083	19.742	0.474
22	0.046	0.042	20.612	0.483
23	0.087	0.086	23.666	0.365
24	-0.027	-0.021	23.958	0.406

Source: Eviews outputs

To ensure the robustness and efficacy of the forecasting process within the study. A fast distinction was made between the dynamic and static forecasts of the oil chain, always within the context of the Arima model. An exogenous variable, which is COVID-19, was introduced and applied as a qualitative variable, by only taking value 0 or 1, to indicate the absence or presence of the pandemic.

Fig.3. Forecast Comparison Graphs (Static and Dynamic)

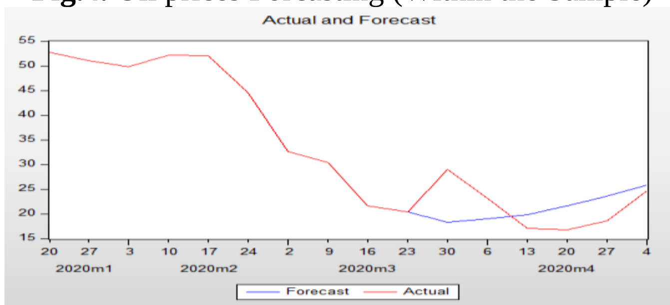


Source: Eviews outputs

It is clear from the results of Fig.3 that the use of STATIC ARIMA forecasting, showing in the left side, provides better expectations, and more appropriate for actual outcomes. By comparison, DYNAMIC forecasts, in the other side, shows a noticeable shift in actual oil data High error margin as shown in the Root Mean Squared Error, Mean Absolute Error and Mean Absolute Percentage Error,
For the DYNAMIC model, Eviews outputs show that both the values of the square root error (12.45721), the absolute error (9.745585) and the absolute percentage error (51128) are very high which indicate an inaccuracy in predicting and moving away from actual values, while STATIC model shows fewer values which indicates that better to predict.
The prediction process is initially started within the sample to test the efficacy of the

model in the forecasting by matching the predicted results with the actuals. Then the sample is moved to include data out of the sample by calculating it. Therefore, data within the sample were chosen from 7/1/2019 to 3/23/2020 inside the model. Results are shown in the table bellow:

Fig.4. Oil prices Forcasting (Within the Sample)



Source: Eviews outputs

From the graph above, the forecasting curve (in blue) is noted differently from the actual from the start of the prediction until April 6, after which the predicted values become very close to the actual. The following table gives the expected and actual values to confirm this:

Table 9. Actual and Forecast Crude Oil Prices for the Period

Date	Price	Pricef
3/30/2020	29	18.32314908367721
04/06/2020	23.190001	18.93379368355418
4/13/2020	17.040001	19.80964716559249
4/20/2020	16.67	21.57944868582973
4/27/2020	18.610001	23.53849540765062
05/04/2020	24.66	25.74654794376931
05/11/2020	30.27	27.96147714689916
5/18/2020	33.889999	30.15301234483275

Source: Prepared by researchers.

The comparison between the table (9) values of the actual price of oil and the forecast price of oil above shows that the values are already approaching each other from the first week of April. Here, we can say that the results obtained are already satisfactory and that the process of predicting 'out of the sample can be carried out using Arima. The following graphs clarify the form in which the forecasted oil prices take from 5/18/2020 to 8/24/2020:

Table 10. Crude Oil Prices Predictions until 8/24/2020

Date	Forecasting price
5/18/2020	30.15301234483275
5/25/2020	32.2328020875048
06/01/2020	34.17759918947285
06/08/2020	35.95892464362943
6/15/2020	37.57100178354857
6/22/2020	39.0112755860331
6/29/2020	40.2857915662985
07/06/2020	41.40319357437898

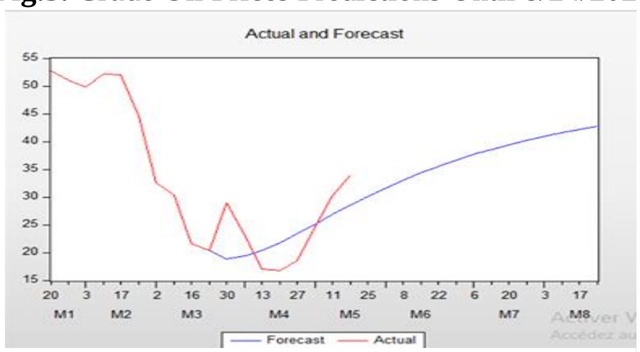
7/13/2020	42.37519177388981
7/20/2020	43.21444466839511
7/27/2020	43.93423122506605
08/03/2020	44.5476237643136
08/10/2020	45.0672131966768
8/17/2020	45.5047915122851
8/24/2020	45.87123100239511

Source: Eviews outputs

According to the ARIMA model results in the table (10) above, oil prices have witnessed a gradual increase over the coming weeks, as oil prices move to the level of forty during June to reach $45 during August. After all, this estimate is relatively relative, and largely related to the extent of the global Corona pandemic's development and its impact on global demand.

From to the forgoing, the predicted values, until 8/24/2020, can now be extracted and the corresponding graphic obtained as following:

Fig.5. Crude Oil Prices Predictions Until 8/24/2020



Source : Eviews Outputs

Conclusion:

Current conditions, in which the world face to because of the COVID-19 outbreak were not at all predictable. The rapid spread of the virus caused a high level of uncertainty and expectations of future economic recession. As a result, the decline in global demand has led to the collapse of many global markets, most notably oil prices, which have experienced a rapid decline since the onset of the pandemic.

In this field, forecasting ARIMA model, the subject of our study, provided satisfactory results on oil price projections. We can therefore accept the main hypothesis of the study.

As the model expected oil prices to rise gradually and settle at 45 US Dollars at the end of august, 2020, this increase might not be satisfactory for oil-exporting countries, but it could be a good indicator of the start of economic recovery. On the other hand, the countries affected should find and activate appropriate policies to stimulate both a rapid and effective growth in order to avoid an escalation of the economic recession.

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