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Abdallah Badr [1], Yassin Eltahir [2]

[1] Statistics Department, Commerce College, Al-Azher University, Egypt

[1,2] Administration Department, Business College, King Khalid University, KSA

[1] abadr@kku.edu.sa

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[1] Statistics Department, Commerce College, Al-Azher University, Egypt
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Abstract: The problem of this study is seeking to answer the question whether the COVID-19 pandemic has a serious effect on the Saudi economy or not. The main objective of the study is to highlight the degree of the Saudi economic flexibility in response to external shocks by using more frequent method, which is long memory technique, that is suitable in analyzing and forecasting such phenomena. By examining the time series of oil prices in the study between November 1990 to December 2020, the series turned out to be unstable and after the first difference stabilized the time series of oil prices. The test of random long series tests turned out to follow random long memory and by comparing between several different models of ARMA models, hence the best model to represent the series was the ARFIMA model (AR=2,d=.469, MA=3) the model was estimated using Eviews10, and the estimated model ARFIMA Model (2, 0.469, 3) was used to predict oil prices in 2021 and the results of the forecast showed that oil prices haven't risen after the COVID-19 pandemic, indicating the strong impact of this pandemic on important strategic commodities, including oil prices. The results are consistent with the theoretical foundations and previous studies which were so reliable in the analysis, interpretation, and prediction of future oil prices .These results confirmed many studies in that it contributes the theoretical and practical debate of the pandemic, hence there is an enhance to future studies.

Keywords: *COVID-19 pandemic; oil prices; long memory model.*

1. Introduction

The impact of the COVID-19 virus and the decline in world oil prices has been reflected in the Saudi budget figures announced on December 15. Oil and non-oil revenues for 2020 fell to 770 billion riyals (about 205 billion dollars), or about 16 percent compared to last year while the deficit increased by 12 percent, or about 298 billion riyals (about 7 79 billion) of GDP.

COVID-19 Pandemic has a burden on the world's economies without exception, but Saudi measures counter its effects more over have contributed in saving the country's economy and providing various support packages (which exceeded 200 billion riyals, or about $ 53 billion), supporting non-oil revenues and reducing operating spending, in addition to delaying or canceling some projects. As most sectors began to recover, this bodes well for better economic indicators in 2021, as revenues grow by 10.3 percent on an annual basis, with improved oil revenues and the huge annual impact of raising the value-added tax. Also, reducing expenses by 7.3 percent on an annual basis will contribute in reducing the budget deficit to 141 billion riyals ($ 37.58 billion)." In 2021, the budget is expected to have a decrease in capital spending by 26.3 percent to 101 billion riyals (26.93 billion dollars) in order to allow more room for the private sector to invest. "

Public debt in Saudi Arabia recorded 34 percent of GDP in 2020 while there was an increase in spending by about 5 percent compared to initial estimates. 2020 was an extraordinary year. COVID-19 also left effects on the 2020 budget by increasing expenditures, especially after the closure measures, as growth declined sharply, and the private sector recorded a decline of -10 percent on the overall average. In manufacturing, social services, construction, restaurants, hotels, retail and telecommunications, the average decline was 5 percent.

Oil is an important strategic commodity. Oil prices contain huge dynamic variables surrounding this commodity; thus, the study of oil prices is one of the most complex studies because in addition to the dynamic variables, there are economic rules that control supply and demand as well as political and climatic conditions. All these matters make studying and forecasting oil prices very difficult.

Consequently, the research problem is represented in finding a quantitative model used as a basis for forecasting oil prices within the COVID-19 pandemic. Accordingly, the research problem can be summarized in the following questions:

- The first question is" what is the most appropriate statistical model to predict oil prices in the presence of the COVID-19 pandemic?"
- The second question is, "is the COVID-19 pandemic affecting Oil Prices?"
- The sub-question: What are the oil prices in the short and long term?

The importance of the research lies in the use of statistical methods that accurately predict oil prices in light of the COVID-19 pandemic and this unprecedented pandemic in history is considered one of the emergent phenomena occurring in the modern era, as its impact extended to all economic activities in the world as a whole, Petroleum globally and in the Kingdom of Saudi Arabia in particular. The research aims to identify the appropriate statistical model through which oil prices can be accurately predicted during and after the pandemic. It measures to which extent the impact of this pandemic extends to oil prices and its impact on global economies, specifically the economy of the Kingdom of Saudi Arabia.

1.1. Research methodology:

The research used the methodology of The Auto-Regressive Model frictional integrated moving average (ARFIMA). It is a suitable model for oil prices, which is characterized by the random long memory phenomenon.

1.2. Literature Review:

Sahid and Mukiddish (2014) took up this in Daddy RaSS use of ARFIMA for the forecasting of 'oil prices'. Given a great importance that oil prices are gaining in the realization of the Barr goals among the 'Economic' development about to all countries which exported or imported it and where that petroleum is considered as an engine 'to the economy.' It forms long memory (ARFIMA) for predicting the prices of the petroleum through the 14 months next beginning from January to Dec 2014. Form ARFIMA, (1,0.465,0) is convenient to represent and predict the prices of petroleum.

Heni boubaker et sghaier (2014) aimed to test the existence of dynamic fractures in both revenues and volatility of oil prices. A set of dual-reproducible long memory models is used for a range of phenomena to suit the dynamic structure of the series being analyzed; among the most important findings of the study are: checking the dynamics of long-term series models in relation to daily returns and changes for oil prices, therefore, I took three pairs of long-series models.

Karia et al. (2012) used (ARFIMA) to predict oil prices (CPO) in Malaysia, which is characterized by their series temporal feature long-term memory and that from thorough evaluation. The two models use some precision statistic scales eg, Root Mean Squares Error (RMSE) and Average Squares Error (MSE).

Mostafaei and Sakhabakhsh (2011) dealt with the prediction of the price of OPEC oil using (ARFIMA). They tested the researcher's style on the Detrended Fluctuation Analysis (DFA) for a series of oil prices for OPEC weekly (through the period of time January 3rd 1997 until June 11th 2010), they have proved evidence on the presence of memory power. The selection form ARFIMA (p, d, q) automatically appreciate using Khandakar-Hyndman algorithm to define p q and d Haslett algorithm and Raftery to appreciate the teacher's basin. The best form is ARFIMA (2,0.34,3) in which it uses it to predict the prices of oil in a OPEC by the end year 2013.

Erfani and Samimi (2009) adopted the prediction of the state of the long-term memory of the stock price index using the (ARFIMA) by using 970 sq% of the daily data during the period of time 26th March 2003 to 8th July 2007 from Tehran Stock Exchange.

Karemera and Kim (2006) came under the heading of evaluation of accuracy in forecasting of models, exchange rates, and ARFIMA (Nominal exchange rates and a comparison of their ability to predict with the structural monetary models and the stochastic flow model, where the monthly data were used for Canada, France, Germany, Italy) from 1973 until December 1998.

The research consists of (4) parts, the first part is the introduction, the second part is the theoretical framework, the third is the analysis of the results, and the fourth part is the results and conclusion.

2. Theoretical Framework

The 'time series analysis' method is considered an important 'statistical' method for forecasting, and this method has been used in many commercial and economic applications. They are processes that have been used on a wide scale in various fields of science, such as astronomy, hydrology, mathematics, computers, finance, and economics. Through its representation of the time series feature, it is characterized by long-term memory -, a new method which contributes to the time series analysis, identifies the quality of its own memory, and then builds an accurate statistical model in future predictions, especially in the case of traditional methods such as fail-style

(ARFIMA(p, d, q)ARIMA). The model has a high reliability, or the model fails to exceed the tests and the checks necessary for the statistical hypotheses.

2.1. Mathematical form of the form: (ARFIMA Model)

ARFIMA forms are models developed by both Granger and Joyeux (1980) and Hosking (1981). They are considered an extension for models $Box\ and\ Jenkins \quad ARIMA$When taking the differential coefficient dTrue values confined to (0.5,0.5-), and its importance is that it allows the modeling of short -term behaviors of the time series through parameters of self-regression and moving averages, and long-term behaviors through parameters of fractional integration.

It is known that the auto-regression model and the integrative moving averages (ARIMA model) can be expressed in the following formula:

$$\emptyset(L)(1-L)^d X_t = \theta(L)\varepsilon_t \tag{1}$$

Where:

$$\emptyset(L) = \left(1 - \sum_{i=1}^{p} \emptyset_i L^i\right) \ ; \ \theta(L)\left(1 + \sum_{j=1}^{q} \emptyset_j L^j\right) \tag{2}$$

V and are respectively polynomials in the parts and for the model, which is finite , and express backward displacement:θ(L)،∅(L)LAR(p)MR(q) L

Where:

$$LX_t = X_{t-1}$$

$$\varepsilon_{t\sim i.i.d.(0,\sigma_\varepsilon^2)}$$

This is known as a 'model'(ARIMA model) just if you took values correct. d

While it can be considered a model ARFIMA for model ARIMA when It takes values that are not correct, allowing the property of long memory to be achieved within the limits of $d0 < d < 0.5$

Definition of:ARFIMA expresses the typical form as follows: ARFIMA(p, d, q)

$$\emptyset(L)(1-L)^d X_t \theta(L)\varepsilon_t \tag{3}$$

Where:

$$\theta(L) = \sum_{j=0}^{q}(-\theta_j)L^j\, , \emptyset(L) = \sum_{i=0}^{qp}(-\emptyset_i)L^i$$

Represent, respectively, the polynomials in$L$ CZain and AR(p)For the model of degree and respectively, is considered to be a `` backward displacement '' effect where it is. MR(q) pqLL$X_t = X_{t-1}$

It is called a process fractional differences when it expresses coefficient fractional differences that are reflected and fixed in the case roots of: $\{X_t\}_{t\in\mathbb{Z}}$d θ(L)،∅(L) Located outside circle unit, and . The white noise process ($|d| < \frac{1}{2}$: $\{\varepsilon_t\}_{t\in\mathbb{Z}}$White Noise), where that:

$$V(\varepsilon_t) = \sigma_\varepsilon^2 \text{ و } \quad E(\varepsilon_t) = 0 \ ; \varepsilon_{t\sim i.i.d.(0,\sigma_\varepsilon^2)}$$

$$.d \in \mathbb{R}$$

represents coefficient of fractional differential and, which can be calculated through the following equation: dd ∈ ℝ

$$(1-L)^d = \sum_{k=0}^{\infty}\binom{d}{k}(-L)^K = \sum_{K=0}^{\infty} b_k L^K \tag{4}$$

Where is:

$$b_0 = 1\ , b_1 = -d \qquad , b_2 = \frac{1}{2}d(1-d)$$

$$b_j = \frac{1}{j}b_{j-1}(j-1-d), \qquad j \geq 3$$

If it was$|d| < \frac{1}{2}$ The $\sum_{k=0}^{\infty}\binom{d}{k}^2 < \infty$, and the process is defined in equation (4) as being practical.

John and Victoria, invertible (2001) for values of, the process is inverted$|d| < \frac{1}{2}(1-L)^d$

We can define, so that it expresses a process. $U_t = (1-L)^d X_t\{U_t\}$ARMA(p, q)

The characteristics can be studied by assuming the state of the model on the figure.ARFIMA(0, d, 0)

Where define a function self-correlation she has as follows: $\rho(k) = {\gamma(k)}/{\gamma(0)} \qquad , \rho(k) = \frac{\Gamma(k+d)(\Gamma(1-d)}{\Gamma(k-d+1)\Gamma(d)}$

Which is written in the following asymptotic form:

$$\rho(k) \sim \frac{\Gamma(1-d)}{\Gamma(d)}k^{2d-1}$$

Notably, 'clarification' is a process ARFIMA (p, d, q) characterized by the long memory when, and the middle memory when,$d \in (0.0,0.5) d \in (-0.5,0.0)$ and memory is short when.

$$d = 0$$

3. Analysis

The study used time series data for oil prices in dollars covering the period from 1990 to 2020, focusing on the impact of the COVID-19 pandemic during the period from the end of 2019 until now. The study period is characterized by that as it had witnessed a number of developments in the global economy. The global oil market has witnessed since the inception of the oil industry in the late nineteenth century and early century, the twentieth, to the end of the current century. From the year 2016, several economic and political situations and changes affected the forces and the size of the oil market in each particular era marked before 1945 AD with the domination of international oil companies and the exploitative and monopolistic control over the economies of the countries.

Developing oil. The period after World War II was marked by rapid expansion of construction and reconstruction, economic recovery in Europe and Japan and the transformation of oil into global fuel. During the period from 1973-1980 the oil market became a monopoly market for the few OPEC countries, and this is what affected OPEC negatively and began to lose its strength. From 1981-2016, the oil market, at this stage, became a competitive market, and was also marked by instability in the economic and political situation, security, and the emergence of globalization. From 2016 to 2020, global oil demand growth declined at a rate of 9% in 2019. It is in the lowest level in nearly eight years. At the end of 2019, the COVID-19 virus appeared, and in 2020, indicating the expansion of the epidemic to reconsider the rates of the decline in oil demand. Consequently, the price fell below zero, which is a precedent that did not occur in the history of oil prices, and oil prices began to recover and gradually rise after the measures taken by countries in the face of the effects of the COVID-19 pandemic and the return of economic activities in most countries of the world to work gradually until it arrived at the end of the year 2020 costs about $ 49.85 on average.

3.1. Characteristics of the data:

In the characteristics of the data, the basic statistics of the data are examined to ascertain the existence of the normality of the data. Therefore, the shape of the data distribution can be determined, which helps in its suitability for examination and analysis as a random time series, and the consequence of that in giving accurate predictive values for the series outside the study period. All this leads to an integrated knowledge of the nature of the variable under study by interpreting its movement according to the proposed statistical model, which is a model (ARIFMA)

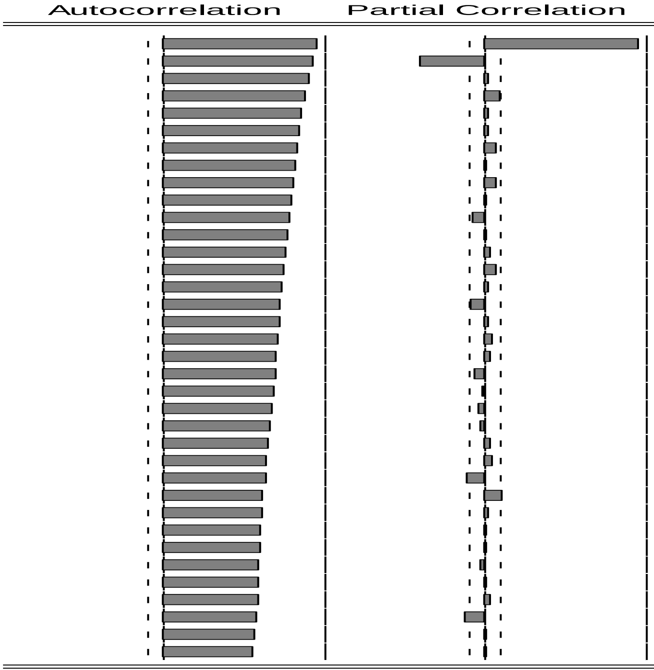
Table (1): Descriptive statistics of time series data

Mean	48.44229
Median	42.07500
Maximum	132.8300
Minimum	10.41000
Std. Dev.	31.07671
Skewness	0.715471
Kurtosis	2.351838
Jarque-Bera	37.22130
Probability	0.000000
Sum	17536.11

Source: prepared by the researcher from E views output

From Table (1), we note that the average oil price during the study period is about 48 dollars, with a large deviation estimated at 31 dollars. The distribution of the data is none -normal, as indicated by the test (Jarque Bera). This statistical result indicates the great turmoil in oil prices during the study period and its fluctuation from one period to another. This indicates a form of a randomness in the time series under study, and thus its suitability for study through statistical time series tools. The values of the coefficient of skewness and kurtosis indicate the non-alignment of the distribution. The positive distortion of the distribution indicates that most real prices below the average may have been affected by long periods of decline compared to the increases, as confirmed by OPEC reports in the recent period.

Sample: 1990M11 2020M12
Included observations: 362



	AC	PAC	Q-Stat	Prob
1	0.988	0.988	356.64	0.000
2	0.968	-0.414	699.29	0.000
3	0.943	0.017	1026.0	0.000
4	0.920	0.099	1337.8	0.000
5	0.899	0.017	1636.3	0.000
6	0.880	0.023	1923.1	0.000
7	0.864	0.070	2200.0	0.000
8	0.849	0.008	2468.5	0.000
9	0.837	0.067	2730.1	0.000
10	0.827	0.014	2985.8	0.000
11	0.816	-0.070	3235.5	0.000
12	0.803	-0.004	3478.5	0.000
13	0.791	0.035	3714.7	0.000
14	0.780	0.067	3944.9	0.000
15	0.770	0.028	4170.3	0.000
16	0.760	-0.087	4390.5	0.000
17	0.750	0.027	4605.4	0.000
18	0.740	0.043	4815.4	0.000
19	0.732	0.036	5021.3	0.000
20	0.723	-0.065	5222.9	0.000
21	0.714	-0.011	5420.0	0.000
22	0.704	-0.035	5611.9	0.000
23	0.691	-0.019	5797.7	0.000
24	0.679	0.038	5977.5	0.000
25	0.669	0.043	6152.3	0.000
26	0.657	-0.122	6321.7	0.000
27	0.647	0.122	6486.3	0.000
28	0.638	0.019	6646.9	0.000
29	0.631	0.012	6804.3	0.000
30	0.625	0.008	6959.4	0.000
31	0.620	-0.020	7112.2	0.000
32	0.614	0.015	7262.7	0.000
33	0.608	0.037	7410.9	0.000
34	0.600	-0.128	7555.7	0.000
35	0.592	0.012	7696.7	0.000
36	0.582	0.001	7833.4	0.000

Figure (1): the plane autocorrelation function
Source: E views output

Out of figure (1), partial autocorrelation analysis indicates the presence of a single bump, which confirms the hypothesis of the existence of the long memory model. This is considered a preliminary test for the existence of the long memory phenomenon. This means that the values degrade slowly compared to the hypothesis of long memory in which the values deteriorate rapidly. Therefore, the autocorrelation function analysis can give a preliminary indication about the presence of the long memory phenomenon in the data through protrusions outside the confidence intervals, as indicated in the table on the autocorrelation function. This initial examination should be accompanied by a deeper examination that reveals the Horst statistic that conclusively determines the severity of the long memory presence in the string data.

3.2. Stationary of the data:

From the output of the data stability test table, the table indicates the instability of the data series in the plane using the Daily Fuller and Daily Fuller augmented test in the plane before the differences. After taking the first difference, the data series were stabilized, as indicated by the Dicky Fuller and Dicke Fuller augmented test results. These statistics and tests on the stability of the series pave the way for sound methods to study the time series and give a general overview about the nature of the series and the extent of its approach to the assumptions related to the time series of economic data. From the stability tests, it can be said that the series data reflects the nature of the economic phenomena that are characterized by fluctuation through the instability of variation and the tendency of the general trend. All this leads to the smoothing of the series through the first differences resulting from the stability of the series as confirmed by the results of the stability tests.

3.3. Better Model to Sample data:

Long memory models are statistical models that represent strong correlations or dependencies between time series data. This type of phenomenon is often referred to as "long-distance memory" or "long-distance addiction." This refers to the permanent correlation between distant observations in the time series. For scalar time series observed at equal time intervals and covariance steady's, this is usually self so that the mean, variance, and autocovariance (between observations separated by lag j) do not change over time. It means that the covariance declines very slowly, like j. It grows so that it can never be totaled. However, you can also refer to specific non-stationary time series, including those with autoregressive unit roots. This shows an even stronger 1 correlation with long lags. Evidence of long memory is often found in economics.

Using (E views) software to extract the best ARMA data model was the best model according to a standard Akaike which is (2.3 After making trial and error attempts) using the computer. Twenty different models have been developed. Standards were calculated Akaike for them, it was found that the model that received the lowest standard Akaike is the model consisting of two slowdowns and three moving averages. Moreover, the different models were evaluated according to the quality regression and correlation test criteria. The following figure shows the different tested models with stats Akaike. Each model and the best model chosen is consistent with the assumptions of economic time-series stability and with the consequent subsequent tests of the series such as examining the long memory model:

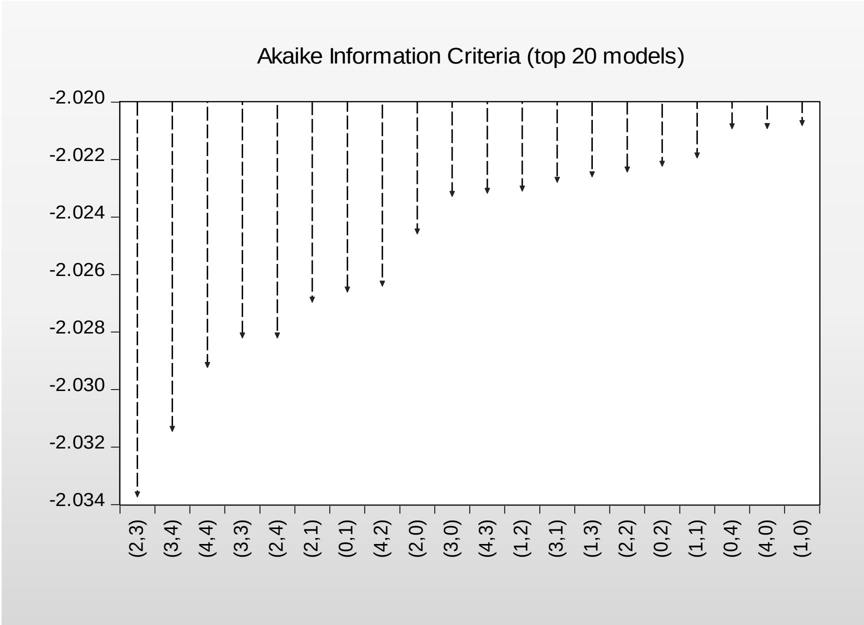


Figure (2): Models ARMA According to standard Akaike
Source: E views output

3.4. Long Memory Model:

Table (2): estimating model ARFIMA Long random memory

Variable	Coefficient	STE	t-Statistic	Prob
C	45.15439	1502.323	0.030056	0.9760
D.	0.497484	0.008353	59.56088	0.0000
AR (2)	0.706104	0.038884	18.15902	0.0000
MA (3)	-0.170409	0.056378	-3.022620	0.0027
SIGMASQ	32.07225	1.555568	20.61771	0.0000
R-squared			0.966699	
Akaike info criterion			6.356228	
F-statistic (2590.828)			Prob (0.000000)	
(Horst coefficient) H			0.969727797	
(Fractional differential coefficient) d			0.469727797	

Source: prepared by the researcher from E views output

From the table above, we note the following:

Constant coefficient refers to the continuous increase in oil prices, the long memory coefficient is positive and significant. The second difference coefficient is positive and significant, and finally the third moving average coefficient is negative and significant. The fractional differential coefficient is equal to (0.469727797) and this indicates the presence of long stable memory in the oil series data during the study period.

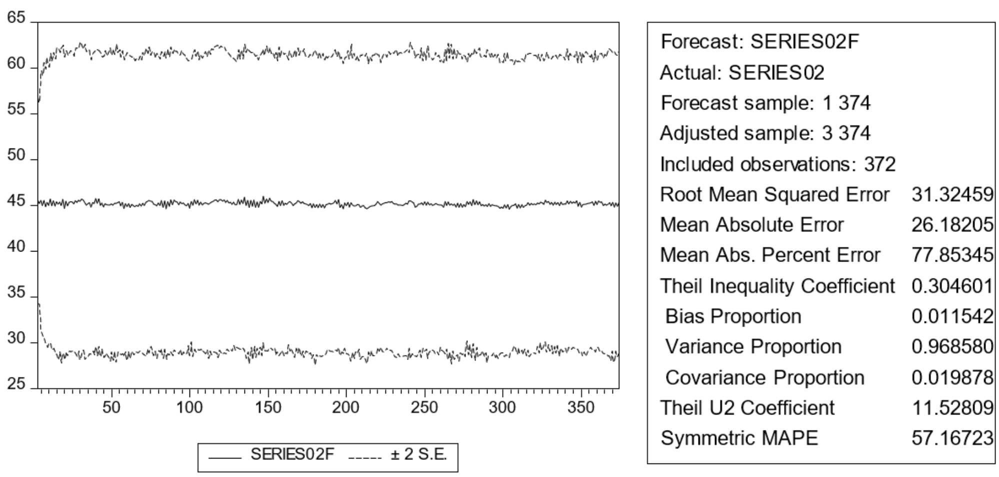


Figure (3): forecasting oil prices in 2021

Summary of the statistical results of the long memory model indicates a significant bug of the model after passing the statistical tests. The oil series during the study period can be used in future oil price forecasting. The inequality prediction test (3) also indicates that the predicted values can be statistically reliable. The table below shows the predictive values of oil prices during 2021 according to the coincident forecasting model.

Table (3): predicted values

Period	forecast value (USD)
January 2021	45
February 2021	45.2
March 2021	45.2
April 2021	45.4
May 2021	45.1
June 2021	45.5
July 2021	44.9
August 2021	45.2
September 2021	45.1
October 2021	45.1
November 2021	45.2
December 2021	45.2

Source: prepared by the researcher from E views output

4. Results and Conclusion

4.1. Search Results:

- Oil prices are characterized by volatility and stability during the study period (November 1990 - December). This result is confirmed from the data analysis.
- Use the power of time in the study period after the oven first, so it was valid to use the Time-series analysis. This result is confirmed from the data analysis.
- Analysis of the self-correlation function and the value of the Horst coefficient proved that the time series of oil prices in the study period is characterized by long memory.
- The ARFIMA model is a convenient model for the time series data of oil prices in the study period. As shown by the results of the model and data processing.
- The results of the model (ARFIMA) are reliable in the interpretation and prediction.
- Forecast values indicate the stability of oil prices during the post-kr pandemic year (there is no rise in oil prices for the post-kr pandemic period) which means that the Saudi economy will be affected like most leading countries in the world.
- Because of the fall in oil prices and that they may continue to fall as predicted values indicate, Saudi Arabia's revenues will be affected and this may be reflected on expenses and economic activity. So it can be said that the pandemic kr has a negative impact on global economies generally and the Kingdom in particular as shown by the results of the study. But as the result of high volume of the reserves in the Saudi economy in form of foreign currency, the Saudi economy can be able to cochin the ramifications of the pandemic.

4.2. Conclusion:

By reviewing the search results, which the COVID-19 pandemic kr contains, it had a significant impact on the oil prices globally in general and Saudi Arabia in particular since the beginning of the pandemic at the end of 2019 and even 2020. The results of the prediction reveal that the impact of the pandemic on oil prices will continue to longer periods. The results indicate that the impact of the pandemic may be continue to several years, hence the ability of each economy to withstand facing the pandemic rest on its structure of the economic, here the small economies may suffer more than the large economies because they could not be able to sustain growing for long years. Here as far as the Saudi economy, it said that the economy is large and well based so the pandemic will result in light effects.

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قياس تأثير جائحة كورونا على أسعار النفط باستخدام نماذج الذاكرة الطويلة (نوفمبر 1990 إلى ديسمبر 2020)

عبدالله بدر[1] ، ياسين الطاهر[2]

[1] قسم الإحصاء- كلية التجارة- جامعة الأزهر- مصر
[2،1] قسم الإدارة- كلية الأعمال- جامعة الملك خالد- المملكة العربية السعودية
[1] abadr@kku.edu.sa

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الملخص:

إن مشكلة هذه الدراسة تسعى للإجابة على سؤال ما إذا كان لوباء الكورونا تأثير خطير على الاقتصاد السعودي أم لا. الهدف الرئيسي من الدراسة هو إبراز درجة المرونة الاقتصادية السعودية في الاستجابة للصدمات الخارجية باستخدام طريقة أكثر تكراراً وهي تقنية الذاكرة الطويلة الملائمة في تحليل وتوقع مثل هذه الظواهر. بدراسة السلسلة الزمنية لأسعار النفط في الدراسة بين تشرين الثاني (نوفمبر) 1990 وكانون الأول (ديسمبر)2020 ، تبين أن السلسلة غير مستقرة، وبعد الاختلاف الأول استقرت السلسلة الزمنية لأسعار النفط. اختبار سلسلة الاختبارات العشوائية الطويلة، اتضح أنه يتبع ذاكرة طويلة عشوائية وبالمقارنة بين عدة نماذج مختلفة من نماذج ARMA ، ومن ثم كان أفضل نموذج لتمثيل السلسلة هو نموذج ARFIMA (AR = 2، d = .469، MA = 3). تم تقدير النموذج باستخدام Eviews10 ، وتم استخدام النموذج المقدر ARFIMA Model (2، 0.469، 3) للتنبؤ بأسعار النفط في عام 2021 وأظهرت نتائج التوقعات أن أسعار النفط لم ترتفع بعد جائحة كورونا، مما يشير إلى قوة تأثير هذا الوباء على السلع الإستراتيجية الهامة، بما في ذلك أسعار النفط. تتوافق النتائج مع الأسس النظرية والدراسات السابقة التي كانت موثوقة للغاية في تحليل وتفسير وتوقع أسعار النفط المستقبلية. أكدت هذه النتائج العديد من الدراسات المتدرب عليها.

الكلمات المفتاحية: جائحة كورونا؛ أسعار النفط؛ نموذج ذاكرة طويلة.