TRENDS AND PERSISTENCE IN GLOBAL OLIVE OIL PRICES AFTER COVID-19

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Abstract

Once the coronavirus pandemic was declared by government authorities in March 2020 and several measures were adopted around the world to limit the effects of COVID-19, the limit agroeconomic processing affected important operations such as not being able to prepare the olive trees for the next harvest. This lack of processes has caused the consumer to perceive an increase in prices due to the shortage of product and the growing demand for olive oil around the world. This research paper, through the use of advanced statistical and econometric techniques, attempts to perform a specific analysis and understand the persistence of the data and the trend of global olive oil prices. Artificial intelligence techniques such as neural network models are also used to predict long-term price behavior. Using ARFIMA (p, d, q) model the results suggest a non-mean reversion behavior, suggesting that the shock is expected to be permanent, causing a change in trend. This result is in line with that obtained using machine learning techniques, where the forecast suggests an increase of the prices around +11.36% in the next 12 months.

Keywords: Global Olive Oil Prices; Fractional Integration, ARFIMA (p,d,q) model; Machine Learning.

JEL Classification: C22; C53; Q11.

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1. Introduction

In shores of Palestine and Syria 6000 years ago olive oil cultivation started, from where its production expanded to Turkey, via Cyprus and then on to Egypt via Crete (see Luchetti, 2002).

According to Muñoz et al. (2015) and confirmed from the data available in the International Olive Council (IOC)[1], the highest concentration of olive oil production is in Mediterranean countries. Some countries from the European Union as Spain (the leader, with almost 45% of the total production in average terms), Italy, Greece, and Portugal represent 65,47% of total production of olive oil in average terms. Also, other southern Mediterranean countries such as Syria, Tunisia, Turkey, Morocco, and Algeria account for 26,3% of total production.

Latin America, Australia and South Africa are some examples of other "non-traditional" olive oil producers/regions around the world. Following Gázquez-Abad and Sánches-Pérez (2009), this fact occurred due to the growth of olive oil world consumption and due to the key element of the Mediterranean diet and its health benefits.

Torres and Maestri (2006), García-González et al. (2010), Gámbaro et al. (2011), Wrege et al. (2015), among others stated that many of these regions have developed their olive oil industry and they achieved to export olive oil.

The effects of the increasing market globalization, the continuous socioeconomic and technological changes, diversification and competition have affected the global olive oil industry (see Petit et al. 2014; Mili, 2016).

Following Lybbert and Elabed (2013), Barjol (2014), Mili (2016), Rodríguez Cohard (2017), among others, stated that due to the increase of the interest in the product among the consumers, the restructuration of the existing plantations and the new orchards in

[1] *https://www.internationaloliveoil.org/wp-content/uploads/2022/12/IOC-Olive-Oil-Dashboard-2.html#production-1*

many olive-growing countries, the economic and technical efforts, the improvement of the cultural and harvesting practices and the modernization of production processes have been determinants for the progressive growth of the global production of olive oil.

On the demand side and in line with Barjol (2014) and Mili (2016), the appeal of the olive oil has spread beyond the Mediterranean due to the reinforced by the public and private promotional campaigns carried out in the non-traditional markets where were stimulating the interest for the olive oil, raising awareness about its health and environmental benefits. So, the product experienced a substantial growth in the three past decades multiplying per 1.8 in volume between 1995-1996 and 2019-2020.

The global consumption of olive oil and its evolution is determined by demand levels in the European Union and their main producing countries. Mili and Bouhaddane (2021) indicated that the 72% of world consumption of olive oil came from consumption in EU countries during the periods 1990-1991 and 2004-2005. However, during the period 2006-2007 and 2019-2020 this share fell to 58% due to lower consumption in the main EU consumer countries that were Spain, Italy and Greece marked by financial crisis and the pandemic crisis.

On the other hand, another trend is observed in the EU non-producing countries as United Kingdom (UK) and Germany, where consumption was 11% in the period 1995-1996 rising to 26% in 2019-2020.

Another country that has experienced a remarkable growth in olive oil consumption has been United States. The consumption in this country on the past 20 years tripled surpassing the position of Greece as the third consumer country (330,000 tons) of olive oil behind Italy and Spain in 2019-2020.

According to Menapace et al. (2011), due to the labels of geographical origins and the consumer preferences, thus can affect to the behavior of olive oil prices around the world.

In accordance with Kohls and Uhl (1990), Siskos et al. (2001), Menozzi (2014), among others, others singularities of this market that may affect to the behavior of olive oil prices are farm production dependence, harvested acreage, weather, soil conditions, climate crisis, value-adding activities, production sustainability, organic and place of origin attributes, adjustment between supply and demand, government incentives, exchange rate, gross domestic product, etc.

A very relevant event worldwide that generated strong doubts about its scope and implications for the global economy and that affected the behavior of the global price of olive oil was the official declaration of the coronavirus pandemic by the World Health Organization. Health (WHO), in March 2020.

With the outbreak of the COVID-19 pandemic, the demand and sale of olive fruit oil consumption experienced a sudden slump, affecting to the global prices. The slowed growth of the industry was caused by the lockdown in various countries and the disruption of trade activities. Just only for the case of United States and according to the U.S. Census Bureau, olive oil imports decreased by 13% in 2020 as compared to those in 2019.

On the other hand, following Francesca et al. (2022) suggest that in the period 2019-2020 in Italy, the production of olive oil was not able to meet national needs, where Italy produced about 300,000 tons compared to 1,000,000 tons of consumption. The reasons for these data were the confinement and limited consumption during this period, the price behavior due to the supply from the large bottling industries and the Spanish market and its behavior.

Francesca et al. (2022) stated that the COVID-19 and its posterior consequences would affect to the olive harvest, affecting to the fall of global production in the Mediterranean basin mainly due to the limit agroeconomic processing affected important operations such as not being able to prepare the olive trees for the next harvest. This lack of processes has caused the consumer to perceive an increase in prices due to the shortage of product and the growing demand for olive oil around the world.

In this context, an imbalance in the production levels of this food source such as olive oil can produce differences in prices. Therefore, understanding the olive oil prices behavior in a cyclical and/or seasonal context can be of great help to farmers and their incomes, consumers, and the policies that need to be implemented to stabilise product prices over the years.

Apart from the research paper mentioned above, there are others that have tried to analyze and to predict future development in global supply and demand (see Mili and Zúñiga, 2001; Anania and Pupo D'Andrea, 2007; Lybbert and Elabed, 2013; Pomarici and Vecchio, 2013; among others). Krystallis and Chryssohoidis (2005), Tsakiridou et al. (2006), Vlontzos and Duquenne (2014), Bajoub et al. (2016), among others, studied the behavior of olive oil production and units of consumption in terms of price variation. They concluded that the production can affect producers and/or consumer alike.

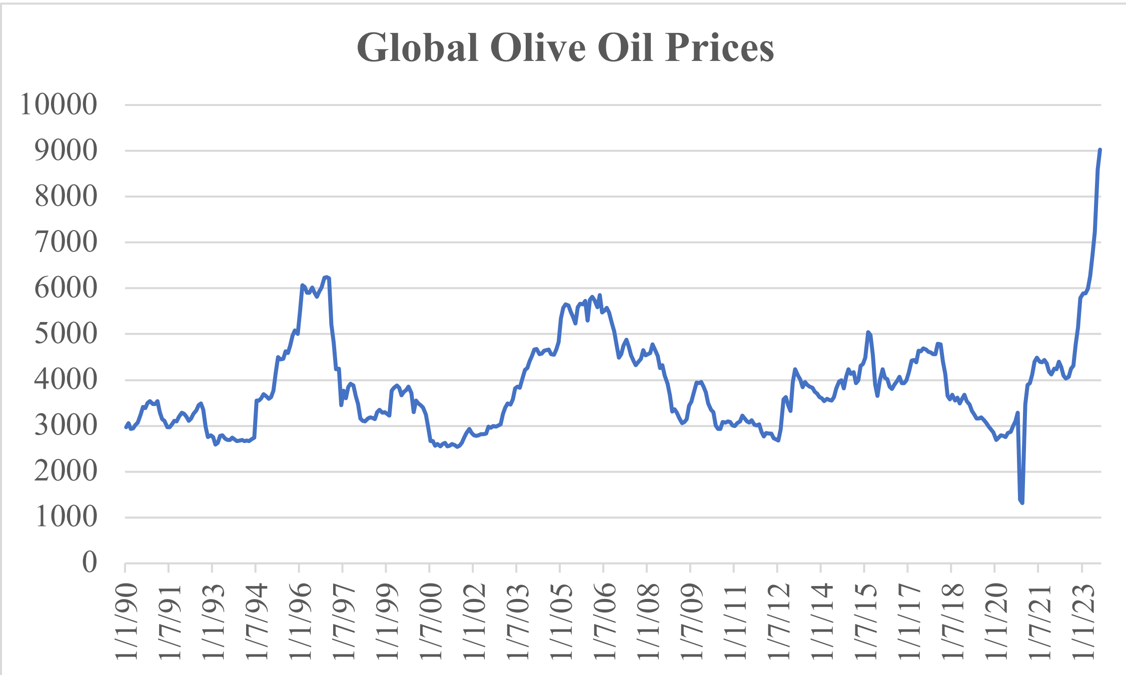
This paper offers several contributions to the scanty literature on time trends and persistence in the olive oil prices behavior. To the best of our knowledge, this paper is the first study to examine persistence in this food source with a high commercial value considering COVID-19 as a structural break. Specifically, this study makes twofold contribution. First it applies long memory techniques to provide evidence on the statistical properties (more specifically, mean reversion and persistence) of global olive oil prices. This is an advantage because is more general than standard approaches based on I(0)/I(1) dichotomy since it allows for fractional values of the integration. Second, we examine the effects of structural break originated by the coronavirus pandemic using an Artificial Neural Network model based on a Multilayer Perceptron (MLP) neural network for time series prediction.

The structure of this paper is as follows. Section 2 describes the data used for our study. Section 3 explains the methodologies used to carry out the research. The results are discussed in Section 4. Finally, the conclusions are found in Section 5.

2. Data

The database used in this research paper was obtained from the Federal Reserve Bank of St. Louis[2]. We use the global price of olive oil in U.S. dollars per metric tons.

The period analyzed is from January 1990 to August 2023 in monthly frequency. The dataset is represented in Figure 1.



The measures adopted by different government to limit the damage caused by COVID-19 and consequently the fall of global production in the Mediterranean basin mainly due to the limit agroeconomic processing affected important operations such as not being able to prepare the olive trees for the next harvest. This lack of processes

[2] *https://fred.stlouisfed.org/series/POLVOILUSDM*

has caused the consumer to perceive an increase in prices due to the shortage of product and the growing demand for olive oil around the world, as we can observe in the figure 1.

3. Methodology

a. Unit roots

Statistics and econometrics use single or multi-equation regression models of time series with the objective to model variables and to understand the interrelations (Box and Jenkings, 1970).

But before to use these types of models, it is important to understand the behavior of these time series. To be able to work with the series, the fundamental assumption is to conclude if the process follows a non-stationary I(1) behavior when it contains a unit root or if it is stationary I(0) when it does not (see Nelson and Plosser, 1982).

So, to determine the integration order of each time series we use standard unit root test. The best known and most widely used unit root test is the Dickey-Fuller test (see Dickey and Fuller, 1979). If a non-systematic component in Dickey-Fuller models is autocorrelated, the Augmented Dickey-Fuller test is constructed (Dickey and Fuller, 1981). Many other tests have been considered due to the greater power, such as Phillips (1987) and Phillips and Perron (1988) in which a non-parametric estimate of spectral density u_t of at the zero frequency has been used. The methodology based on Kwiatkowski et al. (1992) has been used to analyze the deterministic trend.

b. ARFIMA (p, d, q) model

Once we have tested the integration order of each time series by using standard unit root tests, we employ a more advanced methodology. Following the idea that was introduced by Adenstedt (1974), Granger and Joyeux (1980), Granger (1980, 1981) and Hosking (1981), to achieve stationarity I(0), the number of differences does not necessarily have to be an integer value, since it can be any point on the real line and therefore fractional I(d).

So, in order to make the time series stationary I(0), we differentiate the time series with a fractional number. This is an advanced procedure over unit root tests due to the lower power under fractional alternatives (see Dieblod and Rudebusch, 1991; Hassler and Wolters, 1994; Lee and Schmidt, 1996).

Another feature of the I(d) models is to determine and capture the persistence of the observations. This is when observations are far apart in time but highly correlated.

The fractional integrated method that we use in this research paper is the ARFIMA (p, d, q) model where the mathematical notation is:

$$(1 - L)^d x_t = u_t, t = 1, 2, \qquad (1)$$

In equation (1), x_t refers to the time series that has an integrated process of order d ($x_t \approx I(d)$), d refers to any real value, L is the lag-operator ($Lx_t = x_{t-1}$) and $u_t$refers to I(0) which is the covariance stationary process where the spectral density function is positive and finite at the zero frequency and it displays a type of time dependence in the weak form. Therefore, we can state that if u_t is $ARMA\ (p, q)$, x_t is $ARMA(p, d, q)$.

From equation (1), the polynomial $(1 - L)^d$ is expressed in terms of binomial expansion where for all real d, x_t depends not only on a finite number of past observations but also on the whole of its history. So a higher value of d implies a higher level of association between the observations of the series.

Depending on the value of the parameter d, we can differentiate between various cases.

Table 2 summarizes the different results of d:

Table 2. Interpretation of the results of d for the ARFIMA model

$d = 0$	x_t process is short memory
$d > 0$	x_t process is long memory
$d < 0.5$	x_t is covariance stationary
$d \geq 0.5$	x_t is nonstationary
$d < 1$	x_t is mean reverting
$d \geq 1$	x_t is not mean reverting

Although there are several procedures for estimating the degree of long-memory and fractional integration (Geweke and Porter-Hudak, 1983; Phillips, 1999, 2007; Sowell, 1992; Robinson, 1994, 1995a,b; etc.), we follow Sowell (1992) maximum likelihood approach and use the Akaike information criterion (AIC) (Akaike, 1973) and the Bayesian information criterion (BIC) (Akaike, 1979) to select the most appropriate ARFIMA model.

4. Empirical Results

We have calculated three standard unit root/stationarity tests (the Augmented Dickey-Fuller (ADF) test, the Phillips Perron (PP) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test) to analyze the statistical properties of the global olive oil prices.

The results, displayed in Table 1, suggest that the original time series and before and after COVID-19 periods analyzed are all nonstationary I(1). Performing the analysis on the first differences we observe that the series are all stationary I(0). This is something to be expected noting that the above methods only consider integer degrees of differentiation, i.e., 0 for stationary series and 1 for nonstationary ones. Thus, in what follows, we permit more flexibility in the dynamic specification of the model by allowing fractional differentiation throughout the previously described ARFIMA approach.

Table 1. Unit root tests

	ADF			PP		KPSS	
	(i)	(ii)	(iii)	(ii)	(iii)	(ii)	(iii)
Original Data							
Global Olive Oil Prices	0.6837	–1.0326	–1.2611	–0.6174	–0.8572	0.3587	0.1583*
Before COVID-19							
Global Olive Oil Prices	–0.6309	–2.4743	–2.405	–2.3889	–2.3042	0.2772*	0.2037
After COVID-19							
Global Olive Oil Prices	1.5106	–1.718	1.1279	1.1279	–1.0245	0.9414	0.1462

Due to the low power of the unit root methods under fractional alternatives, we also employ fractionally integrated methods, and use ARFIMA (p, d, q) models to study the persistence of the global olive oil prices and its behaviour before and after COVID-19.

The Akaike information criterion (AIC; Akaike, 1973) and the Bayesian information criterion (BIC; Akaike, 1979) are used to select the appropriate AR and MA orders in the models. A point of caution should be adopted here since the AIC and BIC may not necessarily be the best criteria for applications involving fractional models (Hosking, 1981; Beran et al., 1998).

Table 2 displays the estimates of the fractional differencing parameter d and the AR and MA terms, using Sowell's (1992) maximum likelihood estimator of various ARFIMA (p, d, q) specifications with all combinations of p, q ≤ 2, for each time series.

Table 2. Results of long memory tests.

Data analyzed	Sample size (days)	Model Selected	d	Std. Error	Interval	I(d)
Original Time Series						
Global Olive Oil Prices	404	ARFIMA (0, d, 0)	1.16	0.045	[1.09, 1.24]	I(1)
Before COVID-19						
Global Olive Oil Prices	362	ARFIMA (0, d, 0)	1.18	0.047	[1.10, 1.26]	I(1)
After COVID-19						
Global Olive Oil Prices	42	ARFIMA (0, d, 0)	1.02	0.16	[0.76, 1.29]	I(1)

The first results that we find is that the estimates of d in the original time series and the subperiods analyzed have a high degree of persistence, where the value of d is higher than 1 $(d > 1)$ in all cases. So, the time series that includes the entire period analyzed and the subsample analyzed that begins since the pandemic was declared show the same behavior, where the parameter d is equal to 1.02, which means no mean reversion. Therefore, shocks are expected to be permanent, causing a change in trend and thus, extraordinary measures will be required to reverse the situation and recover the original trend.

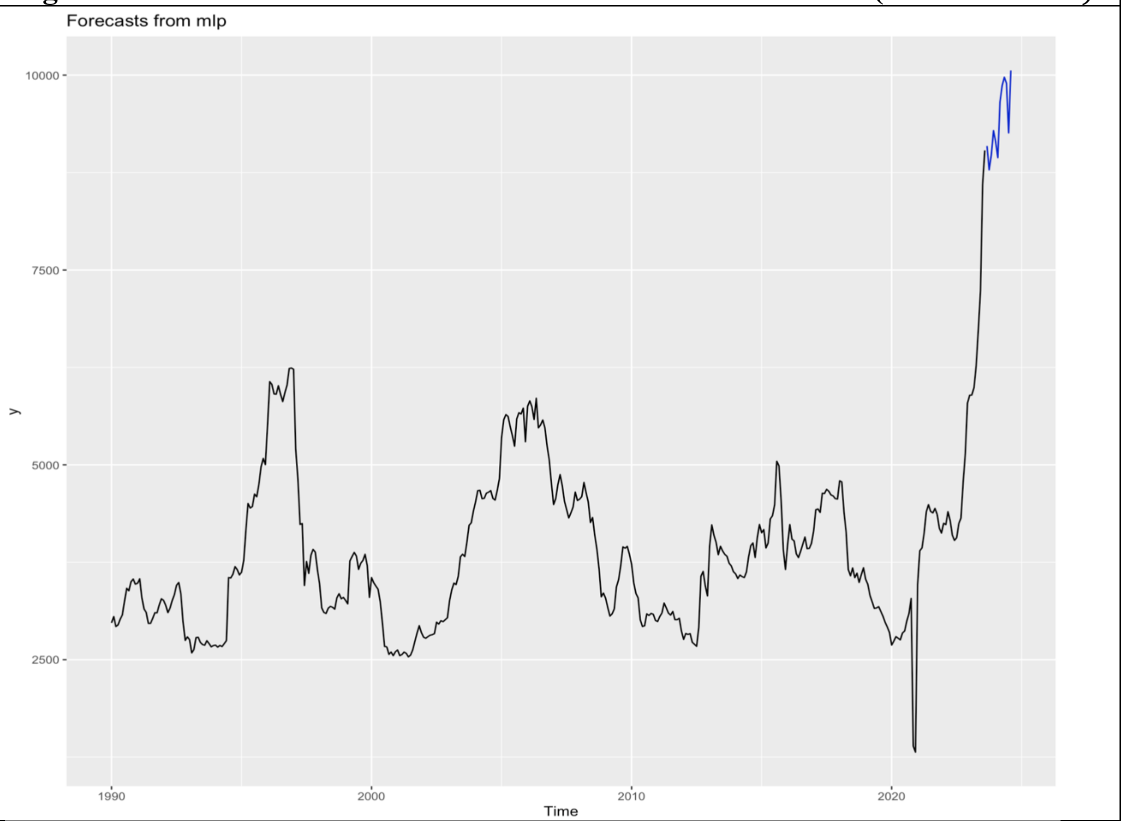
Although the parameter d is 1.02 after COVID-19 period and apparently shows a non-mean reverting behavior, the confidence interval indicates that we cannot reject the $I(d < 1)$ hypothesis for this variable.

Finally, due to the high degree of persistence of time series and its degree of integration, we can use advanced computational intelligence techniques based on machine learning to understand the behavior and the evolution of the global olive oil prices in the future.

For this purpose, we have used the Multilayer Perceptron (MLP) neural network to predict the time-series. The motivation is that the underlying model (non-parametric model) is required to get the results. It also presents interesting features such as its non-linearity. The MLP Neural Network method is based on the back-propagation rule where the errors are propagated throughout the network and allow for the adaptation of the hidden processing elements. It has a massive level of interconnectivity that means that any element of a given layer feeds all the elements of the next layer. It is trained using error correction learning (Güler and Ubeyli, 2005; Martínez et al. 2019; Mapuwei, Bodhlyera, and Mwambi 2020).

The forecasting accuracy using the ANN model is measured by Root Mean Square Error (RSME) and is very close to zero (0.028) what allows us to forecast the digital transformation in financial services industry (Figure 2).

Figure 2. Forecast for Global Olive Oil Prices after COVID-19 ($MSE = 0.448$)



As can be seen, the effects of the measures adopted during the pandemic episode imply an increase in global olive oil prices. Therefore, we expect the prices to go from being worth 9034.55 U.S dollars per metric ton in August 2023 to being worth 10,060.55 U.S dollars per metric ton one year later, that is, +11.36% more.

5. Concluding remarks

A very relevant event worldwide that generated strong doubts about its scope and implications for the global economy and that affected the behavior of the global price of olive oil was the official declaration of the coronavirus pandemic by the World Health Organization. Health (WHO), in March 2020.

Among the affected sectors was the global olive oil industry due to the effects of the pandemic episode.

The measures adopted by different government to limit the damage caused by COVID-19 and consequently the fall of global production in the Mediterranean basin mainly due to the limit agroeconomic processing affected important operations such as not being able to prepare the olive trees for the next harvest. This lack of processes has caused the consumer to perceive an increase in prices due to the shortage of product and the growing demand for olive oil around the world.

There is scarcity literature that analyze the trends and persistence of the global olive oil prices after COVID-19. For this reason, this research paper is the first study that analyzes the statistical properties of the global olive oil prices time series from January 1990 to August 2023, using fractional integration and machine learning techniques.

Using fractional integration methodologies, we see that the results obtained are very persistent and show a similar behavior in the whole sample, and in the subperiods before and after the pandemic period. Focusing on the period in which the pandemic has been declared by government authorities on March 2020, using ARFIMA (p, d, q) model we find that the shock has a permanent component causing a change in trend and therefore extraordinary measures will be required to reverse the situation and recover the original trend.

This result is in line with the argue done by Francesca et al. (2022) about the reduction in the olive oil production would imply an increase in the retail prices and at the wholesale level, affecting to the consumers.

On the other hand, in order to add further accuracy and rigor to this study, we have also used advanced computational intelligence techniques based on machine learning to forecast the global olive oil prices. We have used a machine learning technique based on Multilayer Perceptron (MLP) neural network to verify the previous results. Our forecast is an increase of the prices around +11.36% in the next 12 months due to the low production that occurred during and after the pandemic.

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