Forecasting the competitiveness of Greek olive oil in the international market

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Abstract

This study evaluates and forecasts the competitiveness of the Greek olive oil sector in the world market, using the indicator of relative trade advantage (RTA) by estimating the Box-Jenkins auto-regressive integrated moving average (ARIMA) model. Results based on data over the last fifty years indicate that ARIMA (0,1,2) is the best model to forecast the competitiveness of the olive oil sector in the world agricultural market. According to the short-term forecast, the commercial advantage of Greek olive oil will improve up to 2022, validating the design of holistic value creation strategies to produce competitive advantage under variant products and market conditions.

Keywords: *olive oil, competitiveness, forecasting, Box-Jenkins, ARIMA*
JEL classification: Q1, Q25, M31.

Introduction

Olive cultivation is one of the most important agricultural sectors in Greece which is confirmed by the volume of production in tons and the area of arable land in thousands of acres. In the last 15 years, an average of 2.416 million tons of olives (milled and edible) was produced per year and the average cultivated area was 8.087 million acres with an average yield of 302 kg/ha. The olive oil production in Greece increased (148.48%) from the early 1960s until the end of the 1990s, except for the five years from 1986 through1990, where production declined by an average of 5%. The largest average quantity was during the five years of 1996-2000 and was about 400 thousand tons. The agricultural policy pursued by financial aid and other measures to olive oil producers during that time led to a gradual increase in production. On the contrary, since the beginning of the 2000s production has gradually declined by 12.30% following the implementation of the European Common Organisation of the Market (COM) in olive oil. Europe accounts for 70% of world production on average over the whole period considered. Greece contributes on average 20% of European olive oil production.

In recent decades, the opening of markets at the European and World levels led to the restructuring of both crops and their foreign trade. In particular, after the enlargement of the European Union (EU), new data was created for all countries as trade conditions changed. Undoubtedly, Greek agriculture has been called upon to adapt and operate in an increasingly complex and competitive international environment: First, the implementation of the World Trade Organization (WTO) Agreement has opened up international markets and reduced support for EU products. Secondly, the reform of the Common Agricultural Policy (CAP) has contributed to the increasing support for

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agricultural products. Finally, the enlargement of the European Union (EU) has increased internal competition among its members (Lampropoulou, 2005).

Opening up markets at European and World levels led many scientists and researchers to study the competitiveness and comparative advantage of various products either within a country, between countries (EU-27, OECD countries, etc.), or even concerning the global market. In this evolving economic environment, no one doubts the need to stimulate the competitiveness of every country, which is a complex, multi-stakeholder process. The concept of competitiveness and comparative advantage gains greater value within a unified market, to identify the potentials and weaknesses of each industry, even of each country. The use of different indicators is intended to assess the competitiveness of these industries, as well as the countries themselves. The picture of each industry at the national, and international level, as well as the knowledge of problems, opportunities, and forecast offered, are of interest to economic policy and the relevant market players, so that by applying appropriate strategies they achieve long-term competitiveness, improvement and development.

There is a large number of researchers around the world applying the Box-Jenkins methods in the agricultural sector to predict the production, consumption, exports, and imports of agricultural products in order to adopt appropriate decisions by the relevant authorities (Rahman et al., 2013). This methodology became very popular due to its statistical properties (Zou et al, 2007) during the 1970s. Mandal (2005) used ARIMA models to predict for three years the annual production of cane in India. He found that the implementation of the ARIMA model (2,1,0) was appropriately applied to his data after applying the three stages of the Box-Jenkins methodology. Padhan (2012) also applied the ARIMA models to predict the agricultural productivity of India. For his empirical analysis, he used a set of 34 different products and his data were from 1950 to 2010.Zafeiriou et al. (2012), using the ARIMA model, quantified the production of Mediterranean olive oil for empirical results to be used as a useful tool by policymakers. Hamjah (2014) used the ARIMA model to predict the production of different fruits (banana, guana, and mango) in Bangladesh. He found that the best ARIMA models used in the production of bananas, guanas, and mangoes are ARIMA(3,1,2), ARIMA(1,1,2) and ARIMA (2,1,3) respectively. Rachana et al. (2010) used ARIMA models to predict pea production in India. Saaed et al. (2000) analyzed prospects for wheat production in Pakistan using ARIMA. Diagnostics have shown that the ARIMA (2,2,1) works best. Suleman and Sarpong (2011) published a study with the main aim of forecasting rice production in Ghana, using data from 1960-2010. Rahman et al. (2013) applied the Box–Jenkins methodology to predict lentil production for the years 2011 to 2016 in Bangladesh. Rahman (2017) attempted to predict tea production in Bangladesh by applying ARIMA models and concluded that the most appropriate model appears to be (1,1,2).

The main objectives of this study are: the analysis of the competitiveness of the Greek olive oil exports concerning the international agricultural markets and forecasting of the Greek olive oil exports using the ARIMA model. The specificity of this research is to fit the Box-Jenkins Auto-Regressive Integrated Moving Average to forecast the indicator of the competitiveness of the olive oil sector. The remainder of this paper is structured as follows: The next section presents materials and methods, followed by the results, and the conclusions.

Materials and Methods

Data description

The study used data available on trade flows of Greece and the whole world exports and imports of olive oil from the FAO public database for the period 1961-2014.

Analysis of Comparative Advantage

According to neoclassical economic theory, trade flows are shaped by the comparative advantages and competitiveness of one country over other countries. These two variables can be used as a basis for planning and guiding the appropriate export trade strategy (Vlachos & Patsis, 1998).Competitiveness is an economic phenomenon and because of its complexity, it does not have a universally accepted definition as well as broad consensus. In particular, the interpretation of the concept of 'competitiveness' is confusing when referring to the country level. In contrast, the concept of comparative advantage explains that the specificity of production and profits from commerce are the basis for calculating its yield (Vlachos, 2001; Van der Merwe et al., 2017). The law of comparative advantage refers to the ability of an individual, a business or a country to produce a particular good or service at a lower opportunity cost than other goods or services, respectively. It also refers to the ability to produce a product with the highest relative efficiency, given all other productive products. The overall comparative advantage can determine the overall direction in which the country's investment and trade should follow in order to exploit international differences in product supply and demand (Vollrath, 1991). Also, the comparative advantage explains how trade can create value for both parties when one can produce all goods with fewer resources than the other. The net benefits of such an outcome are called trade profits. However, trade-related assumptions are: perfect competition with efficient markets, homogeneous products, universal access to technology without no learning costs, no externalities or scale economies, technically efficient enterprises, and full employment of resources (Van der Merwe et al., 2017).

Various methods can be used to accept the extent of foreign trade, including the Balassa index, Donges and Riedel index, Hine and Greenaway method, and Sapir method (Van der Merwe et al., 2017). In many studies, the use of the indicator of the Revealed Comparative Advantage (RCA) reveals the comparative advantage of a product from observable trade patterns (Yu et al. 2008). Balassa (1965) was the first to discover the index (RCA) to calculate the comparative advantage using export performance ratios. According to Yu et al. (2008), the utility of the RCA index in comparative studies is limited and problematic. Platania et al. (2015) find that the use of export flows alone may deprive the analysis of significant factors. A more comprehensive index with greater explanatory power was proposed by Vollrath and Vo (1988). Vlachos (2001) reports that Vollrath and Vo developed the Relative Trade Advantage (RTA)index by combining the values of imports and exports. This index is expressed by the following formula:

$$RTA = \frac{\frac{X_{ij}}{X_{Tj}}}{\frac{X_{iW}}{X_{TW}}} - \frac{\frac{M_{ij}}{M_{Tj}}}{\frac{M_{iW}}{M_{TW}}} \qquad (1)$$

Where

X_{ij} = exports value of region j of an agricultural product i to the world;

X_{Tj} =exports value of region j to the agricultural world market;

X_{iW} =exports value of the world in the agricultural product i;

X_{TW} =export value of the agricultural world market;

M_{ij} =imports value of an agricultural product i from the world to region j;

M_{Tj}=imports value of agricultural products to region j;

M_{iW} =imports value of the world in agricultural product i;

M_{TW} = imports value of the agricultural world market.

According to the above formula, RTA is calculated as the difference between the relative export advantage (RXA) and relative import advantage (RMA). RTA incorporates both the relative demand and the relative supply of each commodity, as it combines its export and import values with respect to the world market (Soliman & Bassiony, 2012). The RTA method measures competitiveness under real-world conditions, including unequal economic “playing fields”, distorted economies and varying trade regimes. It is therefore considered to be best suited for measuring the competitive status in the intended study.

Forecasting model for the competitiveness performance of Greek olive oil

To approach the study’s objective on a quantitative outlook of competitiveness of Greek olive oil in the world agricultural market for the following years, a time series of indicators of RTA was generated. It was the autoregressive integrated moving average (ARIMA) model.

Method of Box-Jenkins

Time series analysis with the Box–Jenkins approach is a systematic method of identification, estimation, and diagnostic checking to find an ARIMA statistical model (p, d, q), which represents satisfactorily the stochastic process from which the data were derived. The following three steps are discussed below:

- Identification

The most important step in the process of modeling is to check for the stationarity of the series, as the estimation procedures are available only for stationary series. There are two kinds of stationarity, namely, stationarity in 'mean' and stationarity in 'variance'. A cursory look at the graph of the data and structure of autocorrelation and partial correlation coefficients may provide clues for the presence of stationarity. If the model is 'found to be non-stationary, stationarity needs to be achieved by differencing the series. Stationarity variance could be achieved by some modes of transformation, for example log transformation can be attempted. The next step of identification involves the use of the techniques to determine the values of p, q, and d. The values are determined by using the autocorrelation function (ACF) and partial autocorrelation function (PACF).

- Estimation

According to the Box – Jenkins methods the second stage involves estimating the (p) parameters $a_1, a_2, \ldots, a_p$ of the autoregressive process and the (q) parameters $\theta_1, \theta_2, \ldots \ldots, \theta_q$ of the moving average process. If it is found that the procedure is only autoregressive, then the parameters are estimated using least squares. If, however, the series also contains moving average terms, then non-linear estimation methods are used to estimate the moving average parameters.

- Diagnostic Checking

After having estimated the parameters of a tentatively identified ARIMA model, it is necessary to do diagnostic checking to verify that the model is adequate. Examining ACF and PACF of residuals may show up an adequacy or inadequacy of the model. If it shows random residuals, then it indicates that the tentatively identified model is adequate. The residuals are checked by Box-Pierce's Q statistic, which jointly controls the significance of an m number of autocorrelation coefficients. The null case then would be:

$H_o = p_1 = p_2 = \cdots .. = p_m = 0$, where $p_i i = 1,2, \ldots, m$ are the correlation's coefficients of the residuals.Box-Pierce's Q statistic can be computed as:

$$Q_{BR} = T \sum_{s=1}^{m} \hat{p}_s^2 \qquad (2)$$

where

$\hat{\rho}_s =$ sample residual's correlations;

T= the number of observations

Usually, the number of residual autocorrelations is equal to the square root of the number of observations, i.e.,$m = \sqrt{T}$.Q is distributed approximately as a Chi-square statistic with (p-m-q) degrees of freedom where 'm' is the number of parameters. The null hypothesis is rejected if $Q_{BR} > X_{\alpha}^{2}$, where a is the level of significance.
Subsequently, overfitting is performed, a process by which the suitability of the model is ascertained by comparing it with other higher-order models. For example, we compared the ARIMA model (p, d, q) with the model (p + 1, d, q) and the model (p, d, q + 1). The estimated model is considered most appropriate for our data when the coefficients in the larger models are not statistically different from zero. Also, the most useful forecast evaluation criteria are mean square error (MSE),root mean square error (RMSE), mean absolute error(MAE), root mean square error percentage(RMSPE), mean absolute percentage error (MAPE) and THEIL. Finally, there are other criteria that help in choosing the right model. Two criteria widely used in time series analysis are the Akaike Information Criterion or AIC and the Schwartz Bayesian Criterion or SBC otherwise.

The general form of the ARIMA model (p,d,q) is written as follows:

$$Z = C + (F_1 Z_{t-1} + \cdots + F_p Z_{t-p}) - (\theta_1 a_{t-1} + \cdots + \theta_q a_{t-q}) + a_t \quad (3)$$

where

C =a constant;

$Z_{t-1} \ldots \ldots Z_{t-p}$ =pasts series values (lags);

$F_1 \ldots .. F_p$=coefficients, similar to regression coefficients, to be estimated of the

autoregressive model where autoregressive (AR) model of order p, denoted by AR (p)

is $Z_t = C + (F_1 Z_{t-1} + F_2 Z_{t-2} + F_p Z_{t-p}) + a_t$

$\theta_1 \ldots .. \theta_q$ = coefficients in the moving average (MA) model, where moving average model

of order q or MA (q) is: $Z_t = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} \ldots - \theta_q a_{t-q}$;

a_t = a random variable with zero mean and constant variance.

Results

Calculation of the comparative advantage indices (RTA)

Results of the survey of RTA indices of olive oil export for Greece are presented in Table 1. To this purpose, RTA indices were calculated based on agricultural exports and imports of Greece and the world for the period 1961-2014. Prices higher than one indicate a comparative advantage. The results showed that the olive oil sector in Greece had a comparative advantage in the world market except for the years 1961, 1964, 1970, 1971 and 1973.

Table 1: Prices of the RTA indices for Greek olive oil

1961	-11,96	**1971**	-2,47	**1981**	8,56	**1991**	3,96	**2001**	17,02	**2011**	13,21
1962	6,42	**1972**	4,96	**1982**	24,82	**1992**	30,24	**2002**	12,97	**2012**	16,61
1963	2,53	**1973**	-0,06	**1983**	51,61	**1993**	21,68	**2003**	15,61	**2013**	21,12
1964	0,50	**1974**	1,22	**1984**	43,24	**1994**	20,14	**2004**	5,50	**2014**	10,24
1965	4,29	**1975**	10,18	**1985**	17,19	**1995**	27,92	**2005**	12,87		
1966	5,53	**1976**	6,90	**1986**	29,91	**1996**	26,18	**2006**	12,25		
1967	17,58	**1977**	2,21	**1987**	16,56	**1997**	18,14	**2007**	13,41		
1968	33,07	**1978**	23,70	**1988**	6,13	**1998**	18,11	**2008**	11,81		
1969	8,03	**1979**	12,06	**1989**	36,41	**1999**	26,17	**2009**	12,42		
1970	-9,67	**1980**	7,09	**1990**	20,17	**2000**	14,07	**2010**	11,19		

Source: FAO 2019 and authors' calculation

The maximum price of the RTA indices for Greek olive oil is 51.61 and appeared in 1983, the minimum is -11.95 and appeared in 1961, the average is 14.25 and the standard deviation is 15.69.

Forecast of the relative advantage of Greek olive oil (2015-2022)

- Identification model

Many software packages have the ability for automatic model identification including SPSS (Shukla ,&Jharkharia, 2013).The method of model identification begins by finding out if it is stationary or not by analyzing the graph of ACF. The series is stationary if the graph dies down fast or cuts off fast, else it is not. The non-stationary series has to be converted to stationary by replacing the original series by a series of differences and log transformation. By applying first difference and log transformation, the estimated ARIMA model was (p,1,q). The ACF and PACF plots for the RTA indices of Greek olive oil is presented in Figure 1.

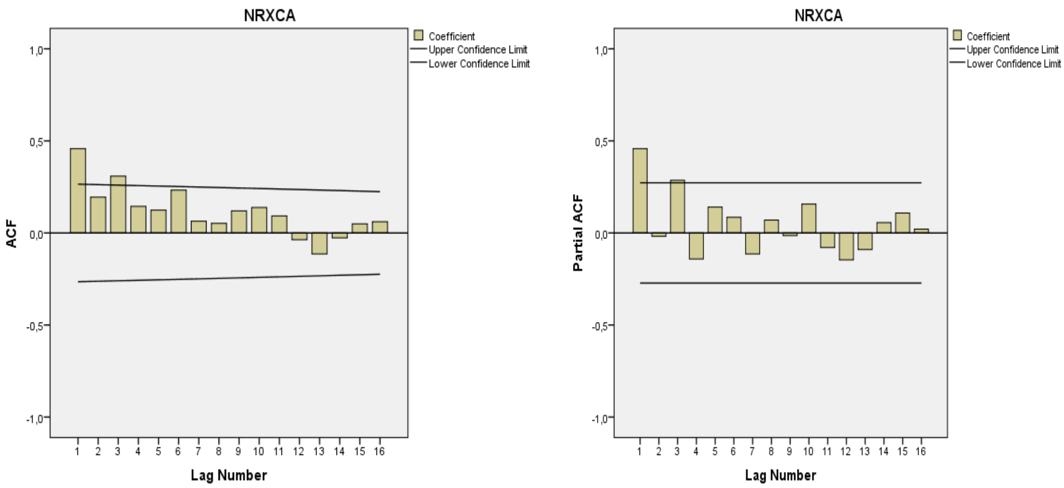

Figure 1: ACF and PACF plots for RTA indices of olive oil

For different values of p and q (0, 1 or 2), various ARIMA models were fitted and appropriate model. According to the Bayesian Schwartz criterion, the appropriate model considered was ARIMA (0,1,2), since it has the lowest value. Correspondingly, with the RMSE and THEIL prediction measures ARIMA (1,1,2) may be considered appropriate (Table 2).

Table 2:Selection of ARIMA models based on RMSE,BIC,MAPE and THEIL

ARIMA MODELS	RMSE	MAE	BIC	MAPE	THEIL
0-1-1	11,073	**7,703**	4,884	188,557	0,03156
0-1-2	10,441	7,777	**4,841**	245,693	0,02976
1-1-2	**10,427**	7,758	4,913	251,655	**0,02972**

1-1-0	11,845	8,400	5,019	188,847	0,03376
2-1-2	10,472	7,794	4,997	244,490	0,02985
1-1-1	10,866	7,597	4,921	214,620	0,03097
2-1-1	10,591	7,904	4,945	**118,958**	0,03019

- Model parameters estimation

The estimators of the relevant parameters of the possible appropriate model ARIMA (0,1,2)were then calculated (Table 3).

Table 3:Model parameters for ARIMA (0,1,2) for RTA indices of Greek olive oil

	Estimate	SE	t	p-value
Constant	0.258	0.350	0.738	0.464
θ_1	0.280	0.130	2.158	0.036*
θ_2	0.5 06	0.129	3.932	0.000*

* represents p-value <0.5

The estimated ARIMA model (0,1,2) was considered the most appropriate. The estimators of the ARIMA model (0,1,2) were found statistically significant since the p-values of the estimators are lower than the level of significance α = 0.05.The theoretical form of the model was:

$$\boldsymbol{Y_t = 0,258 - 0,280\varepsilon_{t-1} - 0,506\varepsilon_{t-2}} \qquad (4)$$

- Diagnostic Checking

To accept the ARIMA model (0,1,2) the residues must be white noise. They should not be autocorrelated. Then, stagnation was performed on the residues of the ARIMA model (0,1,2). With the null hypothesis H0: p = 0 versus the alternative H1: p ≠ 0 at significance level α = 0.05, the null was accepted since all p-values are greater than the significance level α = 0.05. Therefore, there is no autocorrelation, so the residues have white noise behavior.

Finally, overfitting was performed, which is a process of ascertaining the suitability of the model by comparing it with other higher-order models, such as the ARIMA model (1,1,2). It was found that the estimators of ARIMA (1,1,2) are not all significant. Therefore, the most appropriate model is ARIMA (0,1,2).

- Forecasting

After the identification of the model and its adequacy check, it is used to forecast the RTA indices up to 2022.The forecasting results are presented in Figure 2.

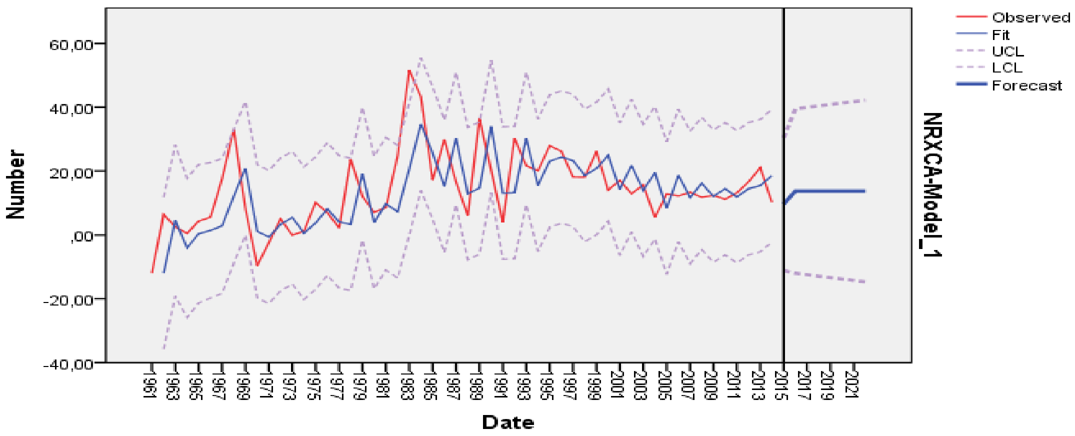

Figure 2:Observed vs. forecast

The RTA of the Greek olive oil sector will exhibit an increase in the period 2015-2022, and so the olive oil will improve the comparative advantage in the world agricultural market in the coming years. Based on preliminary data up to the year 2019, the results seem to adhere to the actual situation.

Conclusions

The economic policy and the relevant market player forces are interested in gaining a clearer picture of each industry at the national, and international level, as well as the knowledge of problems, opportunities and forecasts offered, so that by applying appropriate strategies they can achieve long-term competitiveness improvement and growth.

This paper studies the applicability of ARIMA Models to forecast the comparative advantage of the Greek olive oil sector in the agricultural world market. The novelty of this research is to fit the Box-Jenkins Auto-Regressive Integrated Moving Average to forecast the indicator of the competitiveness of the Greek olive oil sector. In order to achieve this objective, available data on trade flows of Greece and the whole world exports and imports of olive oil were used from the Food and Agriculture Organization (FAO) of the United Nations for the period 1961-2014.For the analysis of competitiveness, the RTA index was selected from the literature. The results showed that the Greek olive oil sector had a comparative advantage in the world market except for the years 1961, 1970, 1971 and 1973.From the study, it was found that ARIMA (0,1,2) is the best model to forecast the competitiveness of olive oil sector in the world agricultural market. According to the short-term forecast, the commercial advantage of the Greek olive oil sector will improve, at least up to 2022,validating the design of Greece's holistic value creation strategies to produce competitive advantage under variant products and market conditions.

The competitiveness of agricultural food products remains an open challenge for the present and the future and especially the oil olive sector due to the importance of the sector in the Greek economy. The world olive oil market is very competitive. Therefore, Greece should adjust its political strategies and implement competitive strategies to take advantage in the international olive oil market.

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