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Changes in productivity in the virgin olive oil sector: An application to Protected Designations of Origin in Spain

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Abstract

Virgin olive oil is a key ingredient of the renowned Mediterranean diet. In this context, the main objective of this study was to estimate and decompose productivity change for Protected Designations of Origin (PDOs) in the Spanish virgin olive oil sector for the period 2008-2013. To this end, we introduced a Luenberger-type indicator based on a specific weighted additive model in Data Envelopment Analysis (DEA), which, in contrast to previous studies, captured all sources of inefficiency and avoided infeasibilities. Regarding the results, we found a reduction in productivity, in average terms, in the first periods analyzed (-0.12 and -1.65), followed by an improvement (0.79 and 0.54), that in the last period analyzed (2012-2013), however, returned to adverse figures (-0.47). In Spain, where foreign competition is weak, the most productive PDOs were those with an important number of oil mills and packaging/marketing companies such as "Montes de Toledo" and "Siurana"; productivity changes were mainly the consequence of downwards and upwards of the frontier of the technology over time. These changes were explained, to a certain extent, by the evolution of the economic crisis; and the productivity of the sector declined, in general, from 2008 to 2010, improving thereafter except for the last registered period, 2012-2013, where expectations for market recovery exceeded actual sales.

Additional key words: data envelopment analysis; additive models; technical change; efficiency change; scale change.

Abbreviations used: BAM (Bounded Adjusted Measure); CRS (Constant Returns to Scale); DEA (Data Envelopment Analys); DMU (Decision Making Unit); EC (Efficiency Change); ECVRS (Efficiency Change under Variable Returns to Scale); GEM (Global Efficiency Measure); MILP (Mixed Integer Linear Program); MIP (Measure of Inefficiency Proportions); PC (Productivity change); PDO (Protected Designation of Origin); PGI (Protected Geographical Indication); RAM (Range Adjusted Measure); SC (Scale efficiency Change); SOS (Special Ordered Set); TC (Technical Change); VRS (Variable Returns to Scale); WADF (Weighted Additive Distance Function).

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Introduction

Olive oil in general, and particularly virgin and extra virgin olive oil, is the cornerstone of the Mediterranean diet, for both their biological and therapeutic value. It has been demonstrated that this diet reduces death rates due to heart disease, the incidence of diabetes, obesity and cancer. To a large degree this potential benefit is due to the presence of olive oil and its chemical composition which is rich in oleic acid, polyphenols, sterols and tocopherols that set it apart from other oils (Moreno & Lezcano, 2015). In addition to the population´s growing concerns related to healthy aspects of food, there is also a growing interest taken in the origin or provenance of products as a source of information and significance in the sale of products and brands (Brugarolas *et al.,* 2010). Without a doubt, one of the most successful formulas that agri-food operators have when it comes to competing in increasingly global markets, consists of emphasising all those aspects related to origin or provenance of products through different figures of protection. These figures are the Protected Designations of Origin (PDOs) and the Protected Geographical Indications (PGIs), both focused on the benefits offered by these geographical indicators, and on the importance of commitment that authorities, whether regional, national, or European are willing to undertake in these matters.

In 2013, Spain has, without including the wine sector, 176 PDOs in food products, the most important of which are virgin olive oil (29). The latter has experienced significant growth in the last decade, by reaching the current 29 from 19, and which have a total number of 761 companies registered, between oil mills, packaging firms and trading companies, a registered surface area of around 700,000 hectares and a total production of around 133,000 tons. In total, the volume of virgin olive oil traded is almost 26,000 tons, which represents a market value of 108 million euros (MAGRAMA, 2014).

It is not usual to come across studies in our country where PDO or PGI efficiency or productivity is analyzed and even less so in the olive oil sector. In this regard, we would like to highlight, first of all, the work carried out by Vidal *et al.* (2014) where the technical efficiency of virgin olive oil PDOs in the 2008-2010 triennium is analyzed, using Data Envelopment Analysis (DEA) models, particularly the BAM (Bounded Adjusted Measure) of Cooper *et al.* (2011b), which allows all possible sources of technical inefficiency to be considered. On the other hand, and in the specific area of productivity, Vidal *et al.* (2015) studied changes in the productivity of these PDOs in the 2008-2013 period by means of global frontiers for each pair of periods analyzed (using the Biennial Malmquist index of Pastor *et al.*, 2011, and a radial model with output orientation). However, it must be borne in mind that the aggregation implies loss of information, which is why our work aims to analyze the PDOs of virgin olive oil in the 2008-2013 six year period, from the perspective of evolution in productivity, thereby offering an alternative to the methodology used in Vidal *et al.* (2015) and therefore not having to resort to the estimation of common frontiers for each pair of years analyzed. Common frontiers help to avoid problems of unfeasibility but with the methodology proposed here, this problem will be solved any way. Furthermore, GEMs (Global Efficiency Measures) are going to be used, in particular a weighted additive model, considering inefficiencies in inputs and outputs instead of using an oriented radial model, as done by Vidal *et al.* (2015). Moreover, given the nature of the additive model, and as a novel element, a Luenberger indicator is defined instead of a Malmquist, measuring the change in productivity that is decomposed not into two but three sources of change: change in efficiency, change in technology and change in scale.

Regarding literature related to the Spanish olive oil industry in general, it is possible to find some recent contributions. Amores & Contreras (2009) proposed an allocation system for subsidies which takes the Agenda 2000 criteria into account through their assignment according to Farm Efficiency which is calculated by decomposing overall efficiency scores, by means of internalizing the externalities of agricultural activity. In particular, this paper analyzes the Type Efficiency of the Andalusian olive-growing sector by applying the proposed indexes over a sample of 3000 real farms. Dios-Palomares & Martínez-Paz (2011) estimated the level of technical efficiency in the Andalusian olive oil industry from a multi-output perspective, and examined olive oil production in quantitative and qualitative terms. Their study also covers the environmental impact of the production process. Dios-Palomares *et al.* (2013) studied the level of technical efficiency in the Andalusian oil industry from a multi-output, non-parametric approach by conducting the DEA methodology with non-radial distance functions, as well as implementing environmental and non-discretionary variables. Finally, Alcaide-López-de-Pablo *et al.* (2014) studied technical efficiency of the olive oil sector in Andalusia (Spain), using a new methodology based on Multi-Criteria Linear Programming. The analysis is developed at global, input and input-consumption sections levels, defining the extent of satisfaction achieved at all these levels for each company, in accordance with their own preferences.

The main objective of this study was to estimate and decompose productivity change for PDOs in the Spanish virgin olive oil sector. To this end, we introduced a Luenberger-type indicator based on a specific weighted additive model in DEA, which, in contrast to previous studies, captures all sources of inefficiency and avoids infeasibilities.

Material and methods

Data envelopment analysis, distance functions and Pareto-Koopmans efficiency

In this paper, we estimated the corresponding technology of each period of time resorting to DEA. DEA is a non-parametric technique based on Mathematical Programming that permits estimating the underlying technology from a dataset of units, usually called DMUs (Decision Making Units), and the distance (technical inefficiency) from these units to the frontier of the estimated production possibility set. In contrast to other alternatives, like Stochastic Frontier Analysis, DEA does not need to specify a particular production function and deals with multiple outputs in an easy way (Cooper *et al.*, 2007).

The measurement of technical inefficiency in the context of multiple-outputs was based on a few measures, fundamentally the Shephard input and output distance function and the directional distance function, in the case of the parametric literature. For the non-parametric literature, the first years of life of DEA witnessed the introduction of many different technical efficiency measures, from the seminal paper of Charnes *et al.* (1978), such as the Russell input and output measures of technical efficiency and their graph extension; the Russell Graph Measure of technical efficiency (see Färe *et al.*, 1985), the weighted additive model (Lovell & Pastor, 1995), the Range Adjusted Measure (Cooper *et al.*, 1999) and the Enhanced Russell Graph (Pastor *et al.*, 1999) or Slacks-Based Measure (Tone, 2001), to name but a few. One of the reasons for the introduction of many different technical efficiency measures in DEA was the piece-wise linear nature of the frontier of the technology. In this context, an important notion was Pareto-efficiency (Koopmans, 1951); indeed, it has been a recurring topic in DEA. In particular, the additive model by Charnes *et al.* (1985) was the first graph linear model that ensured that the evaluated DMU was compared exclusively with respect to the set of Pareto-efficient points in the input-output space. From this model, DEA researchers have introduced some modifications of the original additive model weighting the slacks that appear in the objective function (see, for example, Lovell & Pastor, 1995; Cooper *et al.*, 1999, 2011b; Pastor *et al.*, 2013) in order to measure technical inefficiency using the strongly efficient frontier as a reference, or, what is the same thing, the set of non-dominated points of the corresponding technology. This existence of a different battery of tools for estimating technical inefficiency in the parametric and non-parametric world revealed the importance in DEA in measuring inefficiency with respect to the Pareto-efficient frontier.

The focus of this paper was, in particular, to estimate productivity change over time and decompose this value into technical change, efficiency change and scale efficiency change. Most of the classical results and applications in microeconomics related to the measurement of productivity change over time from panel data were based on the notion of distance function. A distance function behaves as a technical inefficiency measure when an observation belonging to the corresponding technology is evaluated, with a meaning of 'distance' from the assessed interior point to the boundary of the production possibility set. Moreover, another interesting feature of these functions is that they characterize the belonging or not belonging to the technology by means of a sign, as happens with the directional distance function, or by being greater or lesser than one, as in the case of the Shephard distance functions. This feature easily allowed to measure productivity change over time; even in the case of cross-period evaluation when a unit observed in period t+1 under assessment is outside the technology corresponding to period t or vice-versa.

The well-known distance functions in the literature as the input and output Shephard distance functions (Shephard, 1953) and the directional distance function (Chambers *et al.*, 1998), which are used to build the Malmquist index and the Luenberger indicator for measuring productivity change, respectively, neglected slacks since none of them was based on the notion of Pareto-Koopmans efficiency. In order to avoid this problem in DEA, where the existence of a non-smooth boundary of the production possibility set usually generates sources of inefficiency associated with input and output slacks, we introduced and applied in this paper a novel distance function that combines the weighted additive model in DEA with the interesting properties of a distance function.

The weighted additive distance function

Working in the usual DEA framework, let us consider n decision making units (DMUs) to be evaluated. DMU$_j$ consumes $x_j = (x_{1j},...,x_{mj}) \in R_+^m$ amounts of inputs for the production of $y_j = (y_{1j},...,y_{sj}) \in R_+^s$ amounts of outputs. The relative inefficiency of each DMU in the sample is assessed with reference to the so-called production possibility set, which can be non-parametrically constructed from the observations by assuming certain postulates (see Banker *et al.*, 1984). To implement our approach, we will hereafter assume CRS (Constant Returns to Scale). This assumption, when productivity change is the focus, is supported for example by Grifel-Tatjé & Lovell (1995) and Ray & Desli (1997). In this way, the production possibility set in DEA, T, can then be mathematically characterized as follows:

$$T = \left\{ (x,y) \in R_+^m \times R_+^s : x \geq \sum_{j=1}^{n} \lambda_j x_j, y \leq \sum_{j=1}^{n} \lambda_j y_j, \lambda_j \geq 0, j = 1,...,n \right\}. \quad [1]$$

Additionally, we will denote hereafter by means of a superscript the period of time considered.

Next, we introduced the weighted additive distance function (WADF) in a DEA context for estimating the 'distance' from unit $\left(x_k^h, y_k^h\right)$ observed in period h *(h=t, t+1)* to the frontier of technology of period l *(l=t, t+1)*.

$$
\begin{aligned}
D^{l}\left(x_k^h, y_k^h\right) = \quad \max \quad & \sum_{i=1}^{m} w_i^- s_{ik}^- + \sum_{r=1}^{s} w_r^+ s_{rk}^+ \\
s.t. \quad & \sum_{j=1}^{n} \lambda_{jk} x_{ij}^l + s_{ik}^- \le x_{ik}^h, \qquad i=1,\dots,m \quad [2.1] \\
& -\sum_{j=1}^{n} \lambda_{jk} y_{rj}^l + s_{rk}^+ \le -y_{rk}^h, \quad r=1,\dots,s \quad [2.2] \\
& s_{ik}^- \le M\alpha_k, \qquad i=1,\dots,m \quad [2.3] \\
& s_{ik}^- \ge M\left(\alpha_k - 1\right), \qquad i=1,\dots,m \quad [2.4] \\
& s_{rk}^+ \le M\alpha_k, \qquad r=1,\dots,s \quad [2.5] \\
& s_{rk}^+ \ge M\left(\alpha_k - 1\right), \qquad r=1,\dots,s \quad [2.6] \\
& \alpha_k \in \left\{0,1\right\}, \qquad [2.7] \\
& \lambda_{jk} \ge 0, \qquad j=1,\dots,n \quad [2.8]
\end{aligned}
\qquad [2]
$$

where M is a (sufficiently) large positive number and $w^- = \left(w_1^-,\dots,w_m^-\right) \in R_{++}^m$ and $w^+ = \left(w_1^+,\dots,w_s^+\right) \in R_{++}^s$ are weights representing the relative importance of unit inputs and unit outputs. Different paths could be followed in choosing such weights. One possibility selected them based on the observations. In this way, it is possible to achieve a dimensionless optimal value in [2]. This line was followed by Cooper *et al.* (1999) and Cooper *et al.* (2011b) to introduce the Range Adjusted Measure (RAM) and the BAM, respectively.

Program [2] is a Mixed Integer Linear Program (MILP) with a unique binary decision variable, α_k. This model clearly follows the spirit of the traditional weighted additive model (Lovell & Pastor, 1995), where a weighted sum of slacks is maximized. Regarding the constraints, the idea behind the preceding program is the following. On one hand, [2.1]–[2.2] are identical to the first two constraints in the usual weighted additive model. However, in [2] the slacks are free instead of non-negative. Additionally, [2.8] is the usual non-negativity constraint for the intensity variables. Regarding the role played by the binary variable, α_k appears in constraints [2.3]-[2.6], together a sufficiently large positive number, denoted as usual in Mathematical Programming as M. So, we have two possibilities with respect to constraints [2.3] and [2.4] for each input and constraints [2.5] and [2.6] for each output. First, if $\alpha_k = 1$ then the evaluated unit $\left(x_k^h, y_k^h\right)$ is located inside the technology in period l. Accordingly, [2.3] and [2.4] are translated in $0 \le s_{ik}^- \le M$, and [2.5] and [2.6] in $0 \le s_{rk}^+ \le M$. In this case, all the slacks are non-negative as in the original weighted additive model and the objective function also takes non-negative values. Second, if $\alpha_k = 0$ then $\left(x_k^h, y_k^h\right)$ is located outside the technology in period l. Accordingly, [2.3] and [2.4] are equivalent to $-M \le s_{ik}^- \le 0$, and [2.5] and [2.6] to $-M \le s_{rk}^+ \le 0$. In this last case, all the slacks are non-positive and the corresponding objective function is also non-positive. The first scenario is useful to be used when the evaluated unit belongs to the reference technology, whereas the second option is helpful when it is located out of the production possibility set. Since both scenarios are excluding, we have that the sign of the optimal value of [2] will determine whether $\left(x_k^h, y_k^h\right)$ belongs or not to the technology in period l.

Regarding using a sufficiently large positive number M, it is possible to substitute M by a logical relationship that may be computationally implemented by means of a Special Ordered Set (SOS). SOS is a way to specify the number of nonzero solution values among a set of variables without the need of resorting to fixing a big M. The optimizers usually achieve it by using special branching strategies. Traditionally, SOS has been used with discrete and integer variables, but modern optimizers, like for example CPLEX, use also SOS with continuous variables.

One interesting property of the weighted additive distance function is that it is always feasible, even when one works with the cross-period scenario, when a unit observed in period h under assessment $\left(x_k^h, y_k^h\right)$ is outside the technology corresponding to period l, with $h \ne l$. It is due to the fact that there is always a point (observed or virtual) that belongs to the production possibility set in period l that is dominated by $\left(x_k^h, y_k^h\right)$ in the Pareto sense.

Another interesting property is that related to the existence of a correspondence between the distance function and some support function (profit, cost, revenue function). In particular, it can be proved that the Weighted Additive Distance Function (WADF) has a dual relationship with the profit function. This correspondence allows to measure and decompose profit inefficiency into technical and allocative inefficiency (Cooper *et al.*, 2011a).

Nowadays, different alternative distance functions can be appreciated in the literature. The most famous are the Shephard input and output distance functions and the directional distance function. In all these cases, slacks are neglected when the distance function works as a technical efficiency measure. In this sense, as we are aware, the weighted additive distance function is the first one that allows to take into account all sources of technical inefficiency. This justifies the existence of this new approach.

Regarding the weights that we will use in order to solve model [2], it is worth mentioning that we will resort to the weights $w_i^- = 1/(m+s)$, $i=1,\dots,m$, and $w_r^+ = 1/(m+s)$, $r=1,\dots,s$. Nevertheless, from the existing literature, we have several possibilities for selecting the weights: the Measure of Inefficiency Proportions (MIP) (Cooper *et al.*, 1999) considering

$(W^-,W^+)=(1/X_0,1/Y_0)$, where $1/X_0=(1/x_{10},...,1/x_{m0})$ and $1/Y_0=(1/y_{10},...,1/y_{s0})$; the Range Adjusted Measure of Inefficiency (RAM) (Cooper *et al.*, 1999) considering $(W^-,W^+)=(1/(m+s)R^-,1/(m+s)R^+)$ where $R^-=(R_1^-,...,R_m^-)$ with $R_i^-=\max_{1\le j\le n}\{x_{ij}\}-\min_{1\le j\le n}\{x_{ij}\}$, $i=1,...,m$, and $R^+=(R_1^+,...,R_s^+)$ with $R_r^+=\max_{1\le j\le n}\{y_{rj}\}-\min_{1\le j\le n}\{y_{rj}\}$; the BAM of inefficiency (Cooper *et al.*, 2011b) considering $W^-=1/[(m+s)(X_0-\underline{X})]$, where $\underline{X}=(\underline{x}_1,...,\underline{x}_m)$ with $\underline{x}_i=\min_{1\le j\le n}\{x_{ij}\}$, $i=1,...,m$, and $W^+=1/[(m+s)(\overline{Y}-Y_0)]$, where $\overline{Y}=(\overline{y}_1,...,\overline{y}_s)$ with $\overline{y}_r=\max_{1\le j\le n}\{y_{rj}\}$, $r=1,...,s$; the normalized weighted additive model (Lovell & Pastor, 1995) considering $(W^-,W^+)=(1/\sigma^-,1/\sigma^+)$ where $\sigma^-=(\sigma_1^-,...,\sigma_m^-)$ is the vector of sample standard deviations of inputs and $\sigma^+=(\sigma_1^+,...,\sigma_s^+)$ is the vector of sample standard deviations of outputs. Each of them will generate different values for the WADF.

This is not the first time in which weighted additive models are utilized for measuring productivity change in a DEA framework. Grifell-Tatjé *et al.* (1998) defined a quasi-Malmquist using an 'output-oriented' weighted additive model. Unfortunately, they did not propose a decomposition of the index. Chen (2003) showed how to define a non-radial Malmquist index based on an 'input-oriented' weighted additive model. However, this author mixed the Malmquist formulation, multiplicative in nature, with something additive in nature, the selected measure. Additionally, the non-radial index just estimates productivity change partially since it only takes input inefficiencies into account. More recently, Vidal *et al.* (2013) resorted to the BAM (Cooper *et al.*, 2011b), a 'graph' weighted additive model, in order to measure productivity change and its sources from a dataset of the Spanish wine sector. They defined a Biennial Malmquist productivity index (Pastor *et al.*, 2011) from the BAM values. The biennial index considers for each pair of consecutive time periods the common frontier of the pooled data for both periods. In this sense, it uses a methodology based on aggregating data. However, aggregation loses information. In contrast, our approach is a way of using 'graph' weighted additive models for estimating and decomposing productivity change without the necessity of pooling data.

The Luenberger indicator and its decomposition

In many practical situations it is desirable to use measures that are non-oriented in which DMUs are able to change both inputs and outputs. In contrast to the usual Malmquist index, which is based on the input or output Shephard distance functions, Chambers *et al.* (1996) defined the Luenberger productivity change indicator, that is a difference-based index of the directional distance function that accounts for both input contractions and output improvements.

By analogy with the original Luenberger indicator defined through the directional distance function, we next introduce a new Luenberger indicator, which measures productivity change (PC), based on the weighted additive distance function and its corresponding decomposition into efficiency change (EC), scale efficiency change (SC) and technical change (TC).

The productivity change for unit k is estimated as follows:

$$PC_k(t,t+1)=\frac{1}{2}\left[\left(D^t\left(x_k^t,y_k^t\right)-D^t\left(x_k^{t+1},y_k^{t+1}\right)\right)+\left(D^{t+1}\left(x_k^t,y_k^t\right)-D^{t+1}\left(x_k^{t+1},y_k^{t+1}\right)\right)\right] \quad [3]$$

The new Luenberger indicator may then be decomposed into efficiency change - catch-up (EC) and frontier shift (TC):

$$EC_k(t,t+1)=D^t\left(x_k^t,y_k^t\right)-D^{t+1}\left(x_k^{t+1},y_k^{t+1}\right),$$
$$TC_k(t,t+1)=\frac{1}{2}\left[\left(D^{t+1}\left(x_k^{t+1},y_k^{t+1}\right)-D^t\left(x_k^{t+1},y_k^{t+1}\right)\right)+\left(D^{t+1}\left(x_k^t,y_k^t\right)-D^t\left(x_k^t,y_k^t\right)\right)\right] \quad [4]$$

Finally, efficiency change may be further decomposed to identify the contribution of scale efficiency change. To do that, we followed Kapelko *et al.* (2015). By analogy with their aproach, we first define a term that measures efficiency change under Variable Returns to Scale (VRS), denoted as ECVRS.

$$ECVRS_k(t,t+1)=D_{VRS}^t\left(x_k^t,y_k^t\right)-D_{VRS}^{t+1}\left(x_k^{t+1},y_k^{t+1}\right), \quad [5]$$

where $D_{VRS}^l\left(x_k^l,y_k^l\right)$ denotes the optimal value of model [2] with the additional constraint $\sum_{j=1}^{n}\lambda_{jk}=1$.

Scale efficiency change can be then derived as:

$$SC_k(t,t+1)=EC_k(t,t+1)-ECVRS_k(t,t+1) \quad [6]$$

In this way, we get the desired decomposition of productivity change:

$$PC_k(t,t+1)=TC_k(t,t+1)+ECVRS_k(t,t+1)+SC_k(t,t+1) \quad [7]$$

An advantage of the proposed approach with respect to the traditional Luenberger indicator is that mixed period directional distance functions can yield infeasible results (Briec & Kerstens, 2009), while the weighted additive distance function does not suffer from the infeasibility problem.

Data

The units and periods under study are the PDOs of virgin olive oil in Spain and the six-year time frame of 2008-2013. As mentioned in the previous section, there are currently 29 PDOs in this particular sector in Spain. However, after ruling out those that have not provided relevant data to official records or have only done so partially (not covering the six years analyzed), we have found a total of 15 PDOs that have been finally analyzed. Nonetheless, in order to show that the selected units are representative of the whole industry we next report the percentage of total volume of marketed production in the sector for each year analyzed: 78.58% (2008), 83.95% (2009), 82.53% (2010), 74.43% (2011), 81.45% (2012) and 76.97% (2013).

For each PDO, data referring to surface area (hectares), number of oil mills and packaging/marketing companies have been selected, as well as the volume of marketed production (millions of euros) in the period studied (MAGRAMA, 2016). The first three variables will be inputs for the model, while the economic value of production comprises the only output for the model (the main descriptive statistics of these variables appear in Table 1). Our selection of variables is due to two facts. First, it is in line with the variables, inputs and outputs, utilized in the previous studies on Spanish PDOs (see Vidal *et al.,* 2014). Second, al-

Table 1. Main descriptive statistics of virgin olive oil Protected Designations of Origin (PDOs) in the 2008-2013 period. Average (standard deviation).

PDO	INPUTS (average values 2008-2013)			OUTPUT (average value 2008-2013)
	Surface area (ha)	**No. of oil mills**	**No. of packaging/marketing firms**	**Value (M€)**
Aceite Campo de Montiel	31,579.26 (2,546.95)	15.83 (1.67)	8.83 (1.07)	1.16 (0.63)
Aceite de Mallorca	1,658.03 (149.69)	7.00 (0.00)	13.17 (1.86)	1.54 (0.45)
Aceite de Terra Alta	4,108.33 (346.91)	7.33 (2.29)	15.33 (1.80)	2.97 (3.10)
Aceite del Baix Ebre-Montsià	12,111.00 (0.00)	12.00 (0.00)	5.00 (0.00)	0.30 (0.18)
Aceite del Bajo Aragón	19,333.33 (2,702.88)	32.17 (1.57)	14.50 (15.56)	6.31 (0.90)
Aceite de Monterrubio	9,666.67 (745.36)	2.00 (0.00)	2.00 (0.00)	0.26 (0.26)
Baena	60,000.00 (0.00)	19.33 (0.47)	22.00 (0.00)	12.29 (2.52)
Estepa	38,000.00 (0.00)	19.00 (0.00)	3.83 (0.90)	8.49 (1.63)
Montes de Toledo	27,364.93 (1,180.19)	38.50 (3.10)	27.50 (3.30)	1.96 (0.89)
Poniente de Granada	21,410.00 (1,471.33)	12.33 (0.47)	14.17 (0.69)	1.88 (1.23)
Priego de Córdoba	29,628.00 (0.00)	13.50 (0.76)	11.83 (2.03)	6.91 (3.80)
Sierra de Cádiz	28,000.00 (0.00)	7.33 (1.25)	7.67 (0.94)	0.46 (0.78)
Sierra de Cazorla	37,833.33 (745.36)	11.83 (0.37)	13.17 (0.69)	10.31 (3.09)
Sierra Mágina	60,833.33 (372.68)	28.17 (0.37)	24.67 (1.11)	5.37 (0.65)
Siurana	11,971.13 (647.07)	36.50 (1.12)	37.67 (2.69)	15.27 (1.89)

though the literature related to the Spanish olive oil industry in general has resorted to a very different set of variables, we could not directly include the most part of this information because of lack of data on our database (MAGRAMA, 2016). In particular, Amores & Contreras (2009) considered production, employment generated and oil content as outputs and land, productive olive trees, irrigated land for each farm, rain in the farm area (as a non-discretional variable) and total expenses as inputs. Dios-Palomares & Martínez-Paz (2011) utilized olive oil production, a quality index and an environmental management index as outputs and skilled labor, unskilled labor, floating capital, fixed capital and olives milled as inputs. Dios-Palomares *et al.* (2013) used oil, a quality index and an environmental impact index as outputs and milled olives, floating capital, fixed capital and staff costs as inputs. Finally, Alcaide-López-de-Pablo *et al.* (2014) suggested to use olive oil and table olives as outputs and unskilled labor, skilled labor, floating capital and fixed capital as inputs.

Results

The global productivity change of Spanish virgin olive oil PDOs was analyzed. The results are shown in Table 2. A reduction in productivity could be seen, in average terms, in the first periods analyzed, followed by an improvement, that in the last period analyzed, however, returned to adverse figures. This same behaviour of the index was observed for two of the units assessed: Oil from Baix Ebre and Sierra de Cádiz. Additionally, both Montes de Toledo and Siurana presented a more positive trend within all the PDOs analyzed. In particular, the methodology only estimated one biennium with a productive downturn, 2009-2010 in the case of Montes de Toledo (although with a very negative value in productivity change) and 2010-2011 in the case of Siurana. The opposite happened with Sierra de Cazorla, that presented a productive decline between each pair of years, except for the 2011-2012 biennium (see also Fig. 1).

If we closely examine the decomposition of these changes in productivity, and starting with changes in technical efficiency (Table 3), a divergent behaviour to that expressed before could be observed. So, technical efficiency increased in the first part of the six-year period before declining in the last. At the same time, Montes de Toledo stood out as a PDO with ongoing improved productivity in all the time-frame used, while Baena presented the worst of the trends, with three of its indexes in negative (from 2009 to 2012). Finally, both Estepa and Sierra de Cazorla presented zero values for four of their indexes, thereby indicating that both units were technically efficient in the periods in question.

In the case of technological change (Table 4), the behaviour was identical to that of global change, the change even being more intense in the first part of the period. Moreover, in this component of change in productivity, the majority of PDOs presented the same behaviour, except the PDOs of oils from Mallorca, Bajo Aragon, Priego de Córdoba, Sierra de Cazorla and Siurana.

In the case of change in scale (Table 5), the behaviour did not follow the previous trends of alternating improvements and subsequent deteriorations. In any event, the PDOs of Oil from Mallorca, Monterrubio, Estepa, Sierra de Cazorla and Siurana stood out for corresponding to units that operate at an optimal scale (CRS) throughout the whole six-year period.

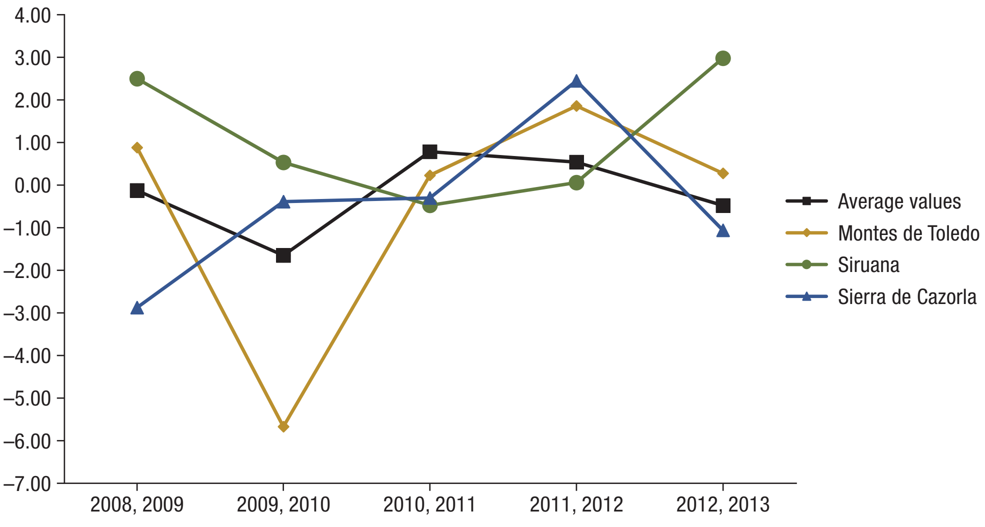

Figure 1. Productivity change of virgin olive oil PDOs in the 2008-2013 period.

Figure 2 shows the evolution of the productivity change and its components over time (on average).

Finally, we compared our results with those obtained from a standard or traditional Luenberger indicator, resorting to the well-known directional distance function. To that end, we reported the corresponding productivity change estimations in Table 6. The estimated trends were similar to those determined by the WADF. However, the determined values for each pair of years and PDO were very different. In order to compare both approaches, we calculated the Pearson's correlation coefficients between each column of Tables 2 and 6, obtaining: 0.8399 for (2008, 2009), 0.3094 for (2009, 2010), 0.7335 for (2010, 2011), 0.8063 for (2011, 2012) and 0.7711 for (2012, 2013). In this way, the results were correlated except for the period (2009, 2010), where the presence of slacks in the optimization models was more important than for the remaining analyzed periods of time.

Discussion

In this paper, we have resorted to a Luenberger-type indicator, based in particular on the weighted additive distance function, for estimating productivity change over time for the 15 considered Spanish PDOs (balanced panel). In contrast to other existing metodologies, the approach utilized presented some advantages: it considered all sources of inefficiency, it was always feasible and it did not aggregate all the units by means of metafrontiers.

As mentioned in the introduction, there are very few studies that analyse changes in productivity of PDOs in the virgin olive oil sector in our country. Our results, and particularly those related to global changes, were consistent with those presented by Vidal *et al.* (2015). The only difference is that experienced in the last biennium analyzed and this is because this work discrimi-

Table 2. Productivity change (PC) of virgin olive oil PDOs in the 2008-2013 period.

PDO	PC (2008,2009)	PC (2009,2010)	PC (2010,2011)	PC (2011,2012)	PC (2012,2013)
Aceite Campo de Montiel	1.30	-2.18	1.01	0.45	-0.51
Aceite de Mallorca	0.03	-1.06	-0.06	1.09	1.10
Aceite de Terra Alta	-2.53	-2.47	0.56	-0.28	1.42
Aceite del Baix Ebre-Montsià	-0.17	-1.65	0.02	0.02	-0.02
Aceite del Bajo Aragón	0.60	-4.87	11.28	-1.04	-11.73
Aceite de Monterrubio	0.05	-0.33	-0.21	0.15	0.28
Baena	-2.21	-1.40	0.17	0.06	3.69
Estepa	-0.56	0.34	1.67	0.18	-1.57
Montes de Toledo	0.89	-5.66	0.23	1.86	0.28
Poniente de Granada	-0.29	-1.58	-1.95	0.23	2.18
Priego de Córdoba	1.60	0.78	-0.06	2.50	-4.09
Sierra de Cádiz	-1.33	-1.43	0.16	0.16	-0.01
Sierra de Cazorla	-2.87	-0.38	-0.30	2.45	-1.06
Sierra Mágina	1.15	-3.37	-0.28	0.25	-0.04
Siurana	2.50	0.54	-0.47	0.06	2.98
Average	-0.12	-1.65	0.79	0.54	-0.47

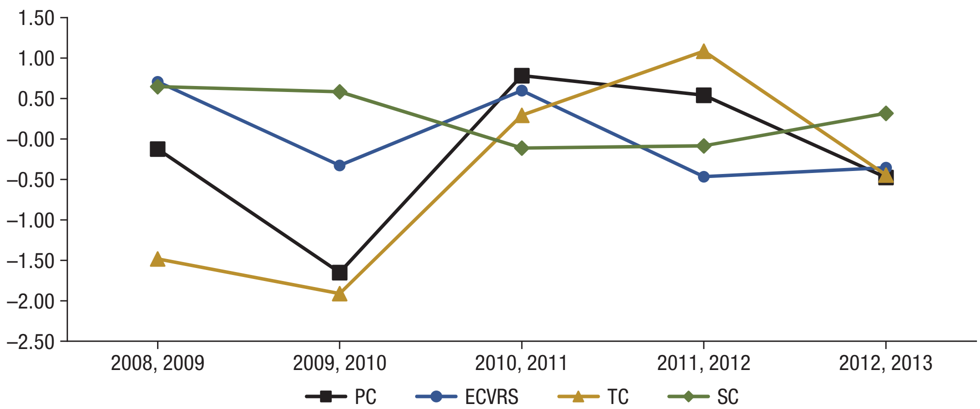

Figure 2. Productivity change (PC), technical efficiency change (ECVRS), technological change (TC), and scale efficiency change (SC) of virgin olive oil PDOs in the 2008-2013 period. Average values.

Table 3. Technical efficiency change (ECVRS: Efficiency Change under Variable Returns to Scale) of virgin olive oil PDOs in the 2008-2013 period.

PDO	ECVRS (2008,2009)	ECVRS (2009,2010)	ECVRS (2010,2011)	ECVRS (2011,2012)	ECVRS (2012,2013)
Aceite Campo de Montiel	1.34	0.39	0.88	-0.04	-0.48
Aceite de Mallorca	0.00	0.00	0.00	0.00	0.00
Aceite de Terra Alta	0.00	-1.89	0.47	-0.92	2.35
Aceite del Baix Ebre-Montsià	-0.08	-0.20	0.11	-0.12	-0.10
Aceite del Bajo Aragón	0.00	-9.79	9.79	0.00	-13.51
Aceite de Monterrubio	0.00	0.00	0.00	0.00	0.00
Baena	4.51	0.00	0.00	-6.35	6.35
Estepa	0.00	0.00	0.00	0.00	0.00
Montes de Toledo	1.34	1.44	0.28	1.21	0.43
Poniente de Granada	0.17	0.91	-1.74	0.00	1.97
Priego de Córdoba	2.13	3.35	0.00	0.00	-2.66
Sierra de Cádiz	-0.88	0.95	0.18	0.06	-0.10
Sierra de Cazorla	0.00	0.00	0.00	0.00	0.00
Sierra Mágina	2.11	-0.02	-0.96	-0.76	0.47
Siurana	0.00	0.00	0.00	0.00	0.00
Average	0.71	-0.32	0.60	-0.46	-0.35

Table 4. Technological change (TC) of virgin olive oil PDOs in the 2008-2013 period.

PDO	TC (2008,2009)	TC (2009,2010)	TC (2010,2011)	TC (2011,2012)	TC (2012,2013)
Aceite Campo de Montiel	-0.18	-2.29	0.22	0.42	-0.25
Aceite de Mallorca	-0.46	-1.42	-0.04	0.23	2.10
Aceite de Terra Alta	-2.53	-2.70	0.19	0.32	-0.13
Aceite del Baix Ebre-Montsià	-0.15	-1.70	0.03	0.04	-0.03
Aceite del Bajo Aragón	0.60	-5.84	0.57	5.33	-3.81
Aceite de Monterrubio	-0.03	-0.35	0.04	0.03	-0.08
Baena	-5.18	-0.79	1.23	3.09	-2.03
Estepa	-0.56	-0.34	1.67	0.18	-1.57
Montes de Toledo	-0.56	-5.88	0.16	0.42	-0.45
Poniente de Granada	-0.56	-1.79	0.23	0.11	-0.36
Priego de Córdoba	-1.01	0.19	-0.06	2.50	-1.04
Sierra de Cádiz	-0.32	-1.44	0.03	0.04	-0.01
Sierra de Cazorla	-2.87	0.38	-0.30	2.45	-1.06
Sierra Mágina	-1.46	-4.12	0.92	1.09	-0.89
Siurana	-6.92	-0.54	-0.47	0.06	2.98
Average	-1.48	-1.91	0.30	1.09	-0.44

nated the different sources of inefficiency to a larger extent; in effect, in the work mentioned earlier, common frontiers (metafrontiers) were estimated, which implies less information motivated by the aggregation of units for different periods, and on the other hand, that the distance calculated by the aforementioned authors was only output-oriented, and, in our case inefficiencies in inputs and outputs were considered simultaneously. What we highlight here for global change, can be applied to the component that measures the technological change experienced by the PDOs.

Furthermore, the results for change in technical efficiency were consistent with those estimated by Vidal *et al.* (2014) for the 2008-2010 period, that is, improvement in technical efficiency under CRS, which is the premise used in this work. This trend also coincided with that observed in Vidal *et al.* (2015).

However, there are no precedents in the literature of the measurement of changes in the scale component. Consequently, this work is the first that addresses the estimation of the evolution of the mentioned source of change in productivity.

The applied methodology has allowed us to show the productivity change trend of each Spanish PDO considered. Although, in general, we observed that the sector experienced a decline from 2008 to 2010, followed by an improvement from 2010 to 2012 and ending with a negative biennium (2012-2013), two PDOs presented better figures with respect to the rest of units: Montes de Toledo and Siurana. Both PDOs are the units

Table 5. Scale efficiency change (SC) of virgin olive oil PDOs in the 2008-2013 period.

PDO	SC (2008,2009)	SC (2009,2010)	SC (2010,2011)	SC (2011,2012)	SC (2012,2013)
Aceite Campo de Montiel	0.14	-0.29	-0.10	0.07	0.21
Aceite de Mallorca	0.49	0.36	-0.02	0.86	-1.00
Aceite de Terra Alta	0.00	2.12	-0.10	0.32	-0.80
Aceite del Baix Ebre-Montsià	0.06	0.25	-0.13	0.10	0.11
Aceite del Bajo Aragón	0.00	10.76	0.91	-6.38	5.59
Aceite de Monterrubio	0.08	0.02	-0.24	0.12	0.36
Baena	-1.54	-0.61	-1.06	3.31	-0.62
Estepa	0.00	0.69	0.00	0.00	0.00
Montes de Toledo	0.11	-1.22	-0.21	0.23	0.29
Poniente de Granada	0.10	-0.70	-0.44	0.12	0.57
Priego de Córdoba	0.49	-2.76	0.00	0.00	-0.39
Sierra de Cádiz	-0.13	-0.94	-0.05	0.06	0.10
Sierra de Cazorla	0.00	-0.77	0.00	0.00	0.00
Sierra Mágina	0.50	0.77	-0.24	-0.08	0.38
Siurana	9.43	1.07	0.00	0.00	0.00
Average	0.65	0.58	-0.11	-0.08	0.32

Table 6. Productivity change (PC) of virgin olive oil PDOs in the 2008-2013 period using the traditional Luenberger indicator.

PDO	PC (2008,2009)	PC (2009,2010)	PC (2010,2011)	PC (2011,2012)	PC (2012,2013)
Aceite Campo de Montiel	1.42	-0.08	2.16	1.07	-1.39
Aceite de Mallorca	0.00	-0.02	0.04	0.09	0.13
Aceite de Terra Alta	-5.00	-2.03	0.04	-0.09	0.08
Aceite del Baix Ebre-Montsià	-0.06	-0.15	0.01	0.01	-0.01
Aceite del Bajo Aragón	1.20	-7.78	5.54	-0.28	-6.21
Aceite de Monterrubio	0.13	0.38	-0.46	0.67	0.26
Baena	-7.45	-1.04	0.21	-0.12	8.23
Estepa	-2.49	-5.16	6.29	1.59	-4.19
Montes de Toledo	-0.12	-0.23	-0.04	0.71	-1.20
Poniente de Granada	1.35	0.12	-0.64	0.12	1.68
Priego de Córdoba	2.47	5.22	-0.12	10.27	-9.40
Sierra de Cádiz	-2.30	1.14	0.35	0.20	-0.02
Sierra de Cazorla	-14.68	1.81	-1.08	10.81	-3.46
Sierra Mágina	1.34	-1.45	-0.47	0.64	0.31
Siurana	1.23	-4.66	-0.55	0.40	2.72
Average	-1.53	-0.93	0.75	1.74	-0.83

with the combination of a larger number of oil mills and packaging/marketing firms, compared to the rest of the units in the sample. The opposite trend is the case of Sierra de Cazorla that experienced drops in its production levels in almost all the periods analyzed and, at the same time, had very high values in surface area, generally speaking, but relatively low values in the combination of oil mills and packaging/marketing firms. In part, the trend globally observed in regard to the evolution of productivity in the six-year period under study is a result of the trend itself, followed by the economic value of the total market production in the sector (sum of the output of the units that make up the sample). This fell drastically in the first few years of the period (from 85.53 M€ in 2008 to 63 M€ in 2010) and remained practically constant in 2011 before picking up again in 2012 (84.5 M€) and 2013 (83.14 M€). These zigzags of the output resulted in periods of downward technology and upward technology trends, as evidenced by the technical change component. This term was the component with the largest value in comparison with all sources of productivity change in the sector for all the periods but 2010-2011, where efficiency change and scale efficiency change presented bigger values. Therefore, we may conclude that the impact of the world economic crisis on the productivity of the sector was negative in its most difficult years (2009 and 2010), leading to improvements mainly in 2012. However, although 2013 was not a bad year regarding revenues, reaching the same level of sales than before the crisis and being slightly lower than the previous year, the number of packaging/retail firms increased considerably from 2012 to 2013 (by 12%), which finally implied a decline in productivity. This increase could have been due to investments in anticipation of a market recovery.

In the future, and when new data become available, the maturity of PDOs in the virgin olive oil sector in Spain should be checked again. Additionally, the new approach could be applied to other PDOs and PGIs, for example in the wine sector, for measuring productivity change over time taking into account all sources of technical inefficiency. Another possible field of application would be the Spanish olive oil industry in general, given the relevance of this sector in Spain.

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