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Efficiency analysis of the designations of origin in the Spanish wine sector

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Abstract

The wine Common Market Organisation has established two concepts for recognizing the quality of wines in the European Union (EU). The first corresponds to the so-called Protected Designation of Origin (PDO), and the second to the Protected Geographical Indication (PGI). The set of Spanish PDOs includes the subset of Spanish DOs (Designation of Origin), which have been recognized as quality wines by Spanish authorities since 1932. Spain accounts for 67 DOs but, due to a lack of data, only 34 of them are suitable for carrying out our analysis. We will analyze the efficiency of this subset for the 2008, 2009 and 2010 seasons resorting to Data Envelopment Analysis (DEA) and using a new additive based efficiency measure known as BAM (Bounded Adjusted Measure). Since we are using panel data, we will also evaluate the productivity associated with this data set resorting to Malmquist indexes. Our results show that the efficiency behavior of the subset of Spanish DOs is uniform over the time periods analyzed and that productivity experiments only minor and irrelevant changes. They also show that three DOs are in a very good competitive position while another three DOs are in a very bad position. We end up suggesting some economic reasons for explaining these results.

Additional key words: additive measure; BAM; DEA; Malquist indexes; productivity; returns to scale.

Introduction

Although Spain has the largest cultivated vineyard area in the world, it is not the largest wine producer; it is third after Italy and France. With respect to exports, Spain is second. In order to increase wine sales, the offer must guarantee its quality. Since the 2008 European Union Commission Regulation on wine markets (OJ, 2008), quality is guaranteed in Spain for the Protected Designation of Origins (PDOs). In Spain, the number of PDOs has increased each year as well as the land associated with them. In the 2008-2009 season, 60% of the land with grapes belonged to PDOs, while in the 2009-2010 season, the percentage increased to 66.2%. Moreover, the production of quality wines is associated mainly to PDOs. Hence, the study of PDOs sheds light on the production of quality wines, a sector that is growing from year to year, being relevant to analyze the performance of such PDOs, in order to learn the main features of the best ones.

To be classified as a DO in Spain, a PDO additionally needs to have the recognition as a quality wine with geographical indication for at least five years. We are going to analyze a subset of 34 DOs, covering a 59.3% of the wine surface of the whole set of Spanish PDOs and being the largest subset with available consistent data. We will evaluate their efficiency resorting to DEA (Data Envelopment Analysis), a non-parametric technique that solves a linear programming problem for each unit being rated.

The efficiency literature related to the wine sector has analyzed farms, cooperatives, firms and agrifood sectors. Farms and cooperatives account for most of the specialized papers, starting with Townsend *et al.* (1998), where wine producing areas in the Western Cape of South Africa have been analyzed. Bojnec &

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Abbreviations used: AR (Autonomous Region); BAM (Bounded Adjusted Measure); CMO (Common Market Organization); CRS (Constant Return to Scale); DEA (Data Envelopment Analysis); DO (Designation of Origin); EU (European Union); PDO (Protected Designation of Origin); PGI (Protected Geographical Indication); VRS (Variable Returns to Scale).

Latruffe (2008, 2009), using panel data, measured farm business efficiency of Slovenian farms. Henriques *et al.* (2009) characterized and analyzed the evolution of wine production for a panel of Portuguese wine farms for the period 2000-2005. Tasevska & Hansson (2010) provided an empirical analysis of the efficiency of 300 family farms in the Tikvesh vineyard district of Macedonia, discovering a large potential for efficiency improvement. Spanish farms have been studied by Arandia & Aldanondo (2007), comparing organic wine farms with conventional ones. Specific papers dealing with cooperatives are by Bonfiglio (2006), Barros & Santos (2007) and Maietta & Sena (2008a,b). Bonfiglio (2006) dealed with Italian agrifood cooperatives while Barros & Santos (2007) studied the Portuguese wine industry, comparing cooperatives with private firms. Maietta & Sena (2008a,b) studied Italian cooperatives and compared them with conventional wine firms, stating that increasing market competition positively affects a coop's efficiency.

Using panel data, Liu & Lv (2010) analyzed the efficiency behaviour of 22 winemaking firms in China. Spanish firms have been studied by Guzman (2004) using accounting variables. Fernández & Morala (2009) studied the cost efficiency of wine firms in the Spanish region of Castilla y León while Sellers-Rubio (2010) used different methodologies, including DEA, in order to compare them with a wide sample of 1,222 Spanish wineries.

Finally, and analyzing agrifood sectors, we report only two papers. Echevarria & Gopinath (2008) analyzed the export behavior of agrifood sectors in Chile, including the wine sector. On the other hand, Fekete *et al.* (2009) studied the efficiency of different agrifood sectors in the four East-European countries known as the Visegrad group, also including the wine sector.

The novelty of our paper is that among the existing specialized literature, no papers have considered a DO as a production unit, as the revision above shows. In other words, quality has not been considered a necessary endogenous feature of the production units in the past. As far as we know, only one paper has considered quality as an exogenous factor and has developed a set of quality indicators in order to evaluate the outputs of wine farms (see Zago, 2009). Moreover, in a highly competitive market, one of the main strategies is the set-up of solid brands. In Spain, there are several brands that are not strong enough under different perspectives. It may be their wine production is too small and they lack the financial resources in order to implement an individual brand strategy. It may also be that their quality has not yet been recognized. Under many circumstances, the DO recognition, which signifies quality and identity, as well as official financial support, constitutes an umbrella-brand that is very convenient for each of its members in order to become competitive. This is, in our opinion, the main reason for analyzing DOs in Spain as proposed in this paper.

The main objective of the paper is to analyze the efficiency of Spanish DOs for the 2008, 2009 and 2010 seasons resorting to Data Envelopment Analysis and using a new additive based measure known as BAM (Bounded Adjusted Measure). We will also evaluate their productivity resorting to Malquist indexes.

Material and methods

At present, and according to the latest provisional data provided by the International Organization of Vine and Wine (OIV, 2010), the global area of vineyard cultivation in 2009 amounted to 7,660,000 million hectares. Spain is the country that still has the largest global area for this crop (1,050,000 ha), followed by France and Italy (840,000 and 818,000 ha respectively). However, if we consider production, with a global volume of 268.7 million hectoliters, the leadership in recent years passed into the hands of France and Italy, with these two being the world's largest producer in 2009 with approximately 18% and 17% of the global volume respectively, followed by Spain at 13%.

As for global consumption of wine ($236 \cdot 10^6$ hL in 2009), France is a major consumer (12.7%), followed by USA (11.6%), Italy (10.4%), Germany (8.6%), China (6%) and the UK (5.4%). Spain ranks sixth as a global consumer at 4.8%. If we refer to global wine exports, with $86.4 \cdot 10^6$ hL in 2009, the leader is Italy with 21.5% of the exports, followed by Spain (16.7%) and France (14.5%). On the other hand, the world's largest importers (with global imports of $83.8 \cdot 10^6$ hL) are led by Germany (16.8%), the UK (14.2%) and USA (11%).

EU Regulation Nº 479 (OJ, 2008) provided the new Common Market Organisation (CMO), which, in relation to European Union quality wines, distinguishes between wines having Protected Designation of Origin (PDO) and Protected Geographical Indication (PGI). In particular, Spain has 83 PDOs, which are characterized by: (i) quality and characteristics are essentially or exclusively due to their geographical origin, with human and cultural factors involved; (ii) 100% of the grapes come exclusively from the production area; (iii) distillation is obtained from varieties belonging to *Vitis vinifera*.

According to the 2008-2009 season data from the Spanish Agriculture Ministry (MARM, 2010a), Spanish PDOs cover 633,498 ha (60% of the national surface devoted to vineyards), and there are 148,899 vine growers and 4,500 wineries. The total volume amounts to more than $11.3 \cdot 10^6$ hL, while sales volume is about $10.3 \cdot 10^6$ hL, of which more than half (54.5%) corresponds to red wine, 16.1% to sparkling wine, 16% to white wine and 7.3% to liquor wine. It is noteworthy that 43% of Spanish wine sold by PDOs is sold abroad. These exports are mainly bottled wine (86.6% *vs.* 13.4% in bulk) and go to EU countries (75%). By country, Germany is the main market for Spanish wines (24.5% of exports), followed by the UK (22.7%), USA (8%) and the Netherlands (7.4%).

The set of Spanish PDOs includes the subset of Spanish DOs, which have been recognized as quality wines by Spanish authorities since 1932. Moreover, the subset of 67 Spanish DOs is the largest within the set of Spanish PDOs. As said before, Spanish DOs are identified by an additional specific characteristic: Table 1 shows different DOs by the Autonomous Regions (AR) they belong to and year of recognition.

Data

For each of the 34 Spanish DOs, data were available for its surface (hectares), the value of domestic sales (in euros) and the value of sales in foreign markets (in euros), the three variables used in our DEA models. The first one is the only input and the last two are the outputs. These data were collected for the 2007/2008, 2008/2009 and 2009/2010 seasons. Since we are dealing with a panel data set, we are able to determine not only the efficiency for each season but also the productivity resorting to a specific Malmquist index. In order to make appropriate economic comments and interpretations, we have also considered other variables, such as number of winegrowers and bulk sales.

The variables used in our DEA models are listed in Table 2. As the reported average, minimum and maximum value for each variable show, our dataset entails large variability. This fact suggests dealing with both variable returns to scale (VRS) and constant returns to scale (CRS) models in order to discover if the size of the DOs really matters, *i.e.,* if scale effects are relevant.

Table 1. Selected subset of 34 Spanish wine designations of origin (DOs) by age and autonomous region (AR)

DO	Name (year of recognition)	AR	DO	Name (year of recognition)	AR
1	Abona (1996)	Canarias	18	Monterrei (1996)	Galicia
2	Almansa (1964)	Castilla-La Mancha	19	Pla de Bages (1997)	Cataluña
3	Binissalem (1991)	Baleares	20	Pla i Llevant (2001)	Baleares
4	Bullas (1994)	Murcia	21	Priorat (1932)	Cataluña
5	Calatayud (1990)	Aragón	22	Rías Baixas (1988)	Galicia
6	Campo de Borja (1977)	Aragón	23	Ribeira Sacra (1997)	Galicia
7	Cataluña (2001)	Cataluña	24	Ribeiro (1932)	Galicia
8	Cava (1986)	Multi-AR*	25	Somontano (1980)	Aragón
9	Chacolí de Álava (2002)	País Vasco	26	Tacoronte-Acentejo (1992)	Canarias
10	Chacolí de Vizcaya (1994)	País Vasco	27	Tarragona (1932)	Cataluña
11	Chacolí de Guetaria (1990)	País Vasco	28	Tierra del Vino de Zamora (2005)	Castilla y León
12	Condado de Huelva (1932)	Andalucía	29	Toro (1987)	Castilla y León
13	Costers del Segre (1988)	Cataluña	30	Utiel-Requena (1932)	Comunidad Valenciana
14	El Hierro (1995)	Canarias	31	Valdeorras (1945)	Galicia
15	La Mancha (1932)	Castilla-La Mancha	32	Valle de Güímar (1996)	Canarias
16	Lanzarote (1994)	Canarias	33	Valle de la Orotava (1995)	Canarias
17	Málaga y Sierra de Málaga (1932)	Andalucía	34	Ycoden-Daute-Isora (1994)	Canarias

Source: Own elaboration based on MARM (2010b) *Multi-AR: Aragón, Cataluña, Comunidad Valenciana, Extremadura, Navarra, País Vasco and La Rioja.

Table 2. Inputs and outputs (for the three seasons)

DO	Input X1 (ha)			Output Y1 (1000€)			Output Y2 (1000€)		
	$X1_{2008}$	$X1_{2009}$	$X1_{2010}$	$Y1_{2008}$	$Y1_{2009}$	$Y1_{2010}$	$Y2_{2008}$	$Y2_{2009}$	$Y2_{2010}$
1	1,123	1,092	1,060	1,100	1,939	2,010	0	0	0
2	7,600	7,118	7,400	1,799	1,690	3,069	3,771	6,534	5,885
3	618	607	614	6,535	6,795	6,174	572.1	805.9	742
4	2,500	2,563	2,300	1,490	1,533	1,395	1,047	562.1	388.4
5	5,135	3,966	3,926	3,156	2,132	2,445	6,707	5,262	6,063
6	7,432	7,413	7,379	11,597	10,110	10,250	16,362	18,349	16,822
7	54,233	50,725	48,337	77,774	70,602	69,510	51,548	53,005	56,327
8	33,085	32,516	30,654	426,268	425,705	418,648	303,407	298,815	324,989
9	46	47	101	743.4	764.9	797.2	136.5	105.6	235.8
10	273	278	358	4,875	5,005	5,794	201.3	197.2	207.6
11	255	400	400	6,340	6,550	6,550	482.5	400.4	582.0
12	3,190	3,202	3,223	10,734	9,061	9,024	89.8	200.5	134.6
13	4,686	4,601	4,696	18,489	14,812	14,996	9,923	7,703	6,613
14	201	192	192	491.5	674.1	263.2	0	0	0
15	186,942	184,509	168,119	51,770	64,769	32,618	96,184	101,120	43,318
16	1,998	1,987	736	422.2	4,465	2,455	15.9	18.6	0
17	1,322	1,338	1,320	9,824	8,805	9,000	4,138	5,397	5,183
18	370	394	386	2,702	3,168	3,463	661.7	737.1	456.9
19	6,993	500	450	2,355	2,355	2,557	651.3	651.3	586.1
20	1,963	315	349	3,449	4,434	4,284	195.6	222.7	375.9
21	1,767	1,817	1,888	8,730	7,605	8,772	9,836	8,584	10,137
22	3,646	3,698	3,814	64,702	72,238	86,293	17,729	15,314	16,855
23	1,222	1,228	1,255	9,112	10,962	10,892	45.7	52.2	68.1
24	2,731	2,750	2,767	11,170	13,761	19,816	355.5	251.8	637.7
25	4,742	4,704	4,644	28,182	26,975	22,234	7,532	7,396	8,506
26	1,552	1,494	1,184	4,542	4,858	4,008	0	3.1	3.1
27	6,249	6,452	6,598	5,325	5,569	7,387	3,025	5,331	2,077
28	766	740	717	617	705.7	747	612.4	789.7	581.3
29	5,900	5,798	5,768	21,446	18,463	16,000	7,932	8,216	5,196
30	41,791	40,761	37,314	12,968	13,304	19,827	27,686	26,491	33,064
31	1,342	1,301	1,286	11,813	11,331	10,495	582.2	493.8	301.3
32	640	570	570	734.3	538.5	842.5	0	0	0
33	616	620	632	794.4	1,914	1,071	0	0	0
34	311	306	264	2,399	2,704	2,326	14.8	28.7	16.5
Avg	*11,327*	*11,059*	*10,351*	*24,248*	*24,597*	*24,1195*	*16,807*	*16,854*	*16,070*
Min	46	47	101	422.2	538.5	263.2	0	0	0
Max	186,942	184,509	168,119	426,268	425,705	418,648	303,407	298,815	324,989

Model specification

Recently, a new efficiency measure was proposed by Cooper *et al.* (2011). It is known as BAM (Bounded Adjusted Measure) and its definition is based on a modification of the additive model, known as the range-bounded additive model. Belonging to the family of the additive models guarantees that the new model accounts for all types of inefficiencies. That means that our model is more accurate than other models that only account for radial (Charnes *et al.,* 1978) or directional (Chambers *et al.,* 1996) inefficiencies. Let us assume that we are dealing with a DEA model with m inputs and s outputs for rating a sample of n units. The range-bounded additive model is obtained by adding to the additive model as much as $m + s$ restrictions. Each added input restriction requires that the projected point of each unit has input values not less than the sample lower bound for each input. Each added output restriction requires that the projected point for each unit have output values not greater than the sample upper bounds of the outputs. The range-bounded additive model is useful when dealing not with a sample but with the whole population. In this case, we assume that any efficient point must be consistent with the bounds defined by the population, and this is precisely what the new additive model requires. Even if we are dealing with a sample instead of the population, resorting to the range-bounded additive model is recommended if the bounds of the sample are the same as the bounds of the population. Deeper insight into our sample of DOs shows that for the only input, grape surface area, it is reasonable to assume that any efficient projection has a surface at least as big as the smallest one in the sample, because it is also the smallest one in the population. Additionally, it is also reasonable to assume that any efficient projection, which represents an ideal DO, has its two sales output values not greater than the corresponding largest output values in the sample, because, in our case, they are also the two largest output values in the whole population. This is particularly relevant for the CRS model because, in the absence of bounds, the projections may lay outside the range of the extreme values associated to the population, which is difficult to assume.

Let us introduce some notation: $\underline{x}_i = \min\{w_{ij}, j = 1,\ldots,n\}$ denotes the range lower bound for input i, $i = 1,\ldots,m$ and $\bar{y}_r = \max\{y_{rj}, = 1,\ldots,n\}$ denotes the range upper bound for output r, $r = 1,\ldots,s$.

The formulation of the CRS range bounded additive model follows:

$$\begin{gathered} Max\left(\sum_{i=1}^{m} s_{io}^{-} + \sum_{r=1}^{s} s_{ro}^{+}\right) \\ s.t. \\ \sum_{j\in E}\lambda_j x_{ij} \le x_{io} - s_{io}^{-},\ i = 1,\ldots,m \\ \sum_{j\in E}\lambda_j y_{rj} \ge y_{ro} - s_{ro}^{+},\ i = 1,\ldots,s \\ x_{io} - s_{io}^{-} \ge \underline{x}_i,\ i = 1,\ldots,m \\ y_{ro} + s_{ro}^{+} \le \bar{y}_r,\ r = 1,\ldots,s \\ \lambda_j \ge 0,\ j = 1,\ldots,n;\ s_{io}^{-} \ge 0,\ \forall\, i;\ s_{ro}^{+} \ge 0 \end{gathered} \qquad [1]$$

Besides the added $m + s$ bound-restrictions, the difference with the usual additive model is that here the projected point is given by $(x_o - s_o^{-},\ y_o + s_o^{+})$, as explained in Pastor *et al.* (2013). Mind also the inequalities in the first two sets of restrictions and the presence of E, which represents the set of efficiency units associated to and identified by the usual additive model. Hence, a preprocessing procedure is needed in order to identify E.

In order to define the efficiency measure BAM under CRS, all we need to do is to substitute the objective function of the last model by the next one.

$$E_c\,(x_o, y_o) = 1 - \frac{1}{(m+s)}\left(\sum_{i=1}^{m}\frac{s_{io}^{*-}}{L_{io}^{-}} + \sum_{r=1}^{s}\frac{s_{ro}^{*-}}{U_{ro}^{+}}\right) \qquad [2]$$

We need to clarify the meaning of the denominators in the last expression, known as "sided-ranges". The new sided ranges are specific for each unit being rated. We define the lower-sided range for input i , $i = 1,\ldots,m$, at unit (x_o, y_o) as

$$L_{io}^{-} = x_{io} - \underline{x}_i \qquad [3]$$

Similarly, we define the upper-sided range for output r, $r = 1,\ldots,s$, at unit as (x_o, y_o)

$$U_{ro}^{+} = \bar{y}_r - y_{ro} \qquad [4]$$

Since each bound is always reached by at least one unit in the sample, certain lower-sided ranges and/or certain upper-sided ranges may be 0 at unit (x_o, y_o). If this is the case, the corresponding ratio in the BAM efficiency measure is set to 0, because the corresponding slack also equals 0 and, consequently, the corresponding contribution to the inefficiency is 0.

For the variable returns to scale case, we simply add the convexity constraint over the set of lambda's, *i.e.*, $\sum_{j\in E}\lambda_j = 1$ and realize, as a consequence, that the two sets of bound can be deleted (see Cooper *et al.*, 2011).

Resorting to the BAM measure is recommended because it is defined for any returns to scale range-bounded model and has interesting properties such as: (i) it accounts for all types of inefficiencies; (ii) it is units invariant, which makes the corresponding linear programming computations well-conditioned; (iii) it is a measure in the range [0,1], with 1 being the score of any efficient unit and 0 the score of any fully inefficient unit; (iv) in the VRS case, its efficiency scores are balanced, in between the radial scores and the Slack Based Measure (SBM) scores (Pastor *et al.*, 1999; Tone, 2001; Cooper *et al.*, 2011). In some sense, the BAM measure incorporates all types of inefficiencies, radial and not radial, but in a way that is smoother than the SBM measure does.

Measuring productivity through biennial Malmquist indexes

One of the lastly defined Malmquist productivity change index is the so-called biennial Malmquist index (Pastor *et al.*, 2011). The reason for choosing the biennial Malquist index is that it does not present any infeasibility under any type of returns to scale and is closer in their results to the adjacent Malquist index than the global Malquist index. Nevertheless we will present only the CRS version of the biennial Malquist index because, as explained later on, its results are really closed to the VRS version in our numerical example. The CRS biennial index considers for each pair of consecutive time periods the common frontier of the pooled data for both periods. Being more precise, for each t we consider two benchmark technologies: The period t technology, T_c^t, and the technology associated with the subsequent period, T_c^{t+1}, defined similarly. Based on these two technologies, the base t biennial technology, T_c^B, can be defined as the convex hull of the period t and period $t+1$ technologies $T_c^B = con\{T_C^t, T_C^{t+1}\}$. The subscript c indicates that all three technologies exhibit CRS. In our specific case for three time periods, there will be two overlapping biennial technologies, one for each pair-wise comparison of adjacent time periods. The biennial Malmquist index is defined specifically for the adjacent time periods t and $t+1$ since two adjacent time periods are sufficient to establish the desirable properties of allowing technical regress and progress, and maintaining previous productivity calculations. (These two properties do not hold for the Sequential or the Global Malmquist indexes, as explained in the last mentioned paper).

Based on the CRS BAM efficiency score for (x,y) relative to the period t technology, $E_c^t(x,y)$, the standard adjacent output oriented period t Malmquist index for producer j is given by

$$M_c^t(x_j^t, y_j^t, x_j^{t+1}, y_j^{t+1}) = \frac{E_c^t(x_j^t, y_j^t)}{E_c^{t+1}(x_j^{t+1}, y_j^{t+1})} \qquad [5]$$

The period $t+1$ Malmquist index is defined similarly, considering the corresponding efficiency score relative to the technology for period $t+1$, E_c^{t+1}. Usually, M_c^{t+1} differs from M_c^t, which leads to the definition of the adjacent Malmquist productivity change index (Caves *et al.,* 1982), M_c, as the geometric mean of M_c^t and M_c^{t+1}:

$$M_c(x_j^t, y_j^t, x_j^{t+1}, y_j^{t+1}) = [M_c^t(x_j^t, y_j^t, x_j^{t+1}, y_j^{t+1}) \times M_e^{t+1}(x_j^t, y_j^t, x_j^{t+1}, y_j^{t+1})]^{1/2} \qquad [6]$$

Similar to the definition of $E_c^t(x,y)$, we define the biennial efficiency score, E_c^B, based T_c^B on instead of T_c^t. We further define the biennial CRS Malmquist index for producer j as

$$M_c^B(x_j^t, y_j^t, x_j^{t+1}, y_j^{t+1}) = \frac{E_c^B(x_j^t, y_j^t)}{E_c^B(x_j^{t+1}, y_j^{t+1})} \qquad [7]$$

Since we are using the biennial CRS technology, which includes both the period t and period $t+1$ technologies, we do not need to resort to any geometric mean when defining [7].

What remains is to decompose M_c^B into two factors, efficiency change, EC_c^B, and technological change, TC_c^B. The efficiency change is, as usual, defined as

$$EC_c^B = \frac{E_c^t(x_j^t, y_j^t)}{E_c^{t+1}(x_j^{t+1}, y_j^{t+1})} \qquad [8]$$

while the technical change factor corresponds to what is left over:

$$TC_c^B = \frac{M_c^B}{EC_c^B} \qquad [9]$$

Results

Efficiency indexes have been obtained using VRS and CRS BAM models for the last three seasons. For the sake of simplicity, we will denote the three consecutive seasons as 2008, 2009 and 2010. The different efficiency indexes are reported in Table 3, with three decimal places. Columns 2, 3 and 4 report the results of the CRS models, while columns 5 to 7 report the VRS model results. The last three columns report the scale efficiency that measures —as a ratio— the differences between both models. If scale efficiency is close to 1, both models are similar and size does not matter. This is exactly what happens in our analysis for the three considered seasons.

For the CRS models, only DO8 (Cava) is always efficient. In second place, DO22 (Rías Baixas) is efficient in 2009 and 2010 and slightly inefficient in 2008. In third place, DO11 (Chacolí de Guetaria) is efficient only in 2008. In terms of surface, D08 is the fourth biggest DO while D11 is the second smallest. The remaining DOs are inefficient (although DO9 is almost efficient in the three periods) with three strongly inefficient units throughout the period: DO15 (La Mancha) with efficiency scores in the range 0.059 and 0.061, DO7 (Cataluña) with scores between 0.203 and 0.214, and DO30 (Utiel-Requena) with scores ranging from 0.264 to 0.274. Nonetheless, the rest of 28 inefficient DOs have scores in the range 0.665 and 0.999. It is rather curious that the three biggest DOs are the three strongly inefficient units, while the fourth biggest DO is the only fully efficient unit. Moreover, two out of the other three almost efficient units over the three seasons are small DOs (DO11 and DO9). The fully efficient unit, DO8, is the sales leader in both the domestic and foreign markets. Nevertheless, units DO15 and DO7, which are second and third in total sales ranking in 2008 and 2009, are the most inefficient units.

Table 3. Efficiency scores for constant return to scale (CRS) and variable returns to scale (VRS) models (2008, 2009 and 2010)

DO	CRS			VRS			Scale (SC)		
	CRS_{2008}	CRS_{2009}	CRS_{2010}	VRS_{2008}	VRS_{2009}	VRS_{2010}	SC_{2008}	SC_{2009}	SC_{2010}
8	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
22	0.973	1.000	1.000	1.000	1.000	1.000	0.973	1.000	1.000
11	1.000	0.938	0.876	1.000	0.945	0.944	1.000	0.993	0.928
9	0.999	0.999	0.998	1.000	1.000	1.000	1.000	1.000	0.999
10	0.887	0.968	0.867	0.893	0.978	0.947	0.993	0.989	0.915
21	0.861	0.830	0.823	0.867	0.836	0.837	0.994	0.993	0.983
17	0.810	0.818	0.795	0.811	0.820	0.811	0.999	0.997	0.980
3	0.796	0.845	0.778	0.796	0.849	0.818	1.000	0.995	0.951
31	0.777	0.806	0.767	0.801	0.808	0.783	0.970	0.998	0.979
20	0.769	0.890	0.785	0.778	0.899	0.870	0.988	0.990	0.903
25	0.766	0.768	0.747	0.774	0.769	0.750	0.991	0.999	0.995
18	0.759	0.781	0.727	0.768	0.791	0.802	0.988	0.987	0.907
23	0.757	0.809	0.774	0.770	0.811	0.791	0.983	0.998	0.979
13	0.753	0.736	0.721	0.753	0.737	0.725	1.000	0.999	0.994
6	0.736	0.742	0.725	0.737	0.743	0.728	0.999	0.999	0.996
29	0.734	0.732	0.708	0.737	0.732	0.712	0.997	0.999	0.996
34	0.730	0.784	0.670	0.744	0.794	0.802	0.981	0.987	0.835
19	0.723	0.727	0.682	0.730	0.734	0.740	0.991	0.989	0.922
24	0.716	0.745	0.760	0.726	0.746	0.767	0.987	0.999	0.992
5	0.707	0.707	0.703	0.708	0.710	0.710	0.998	0.996	0.991
12	0.707	0.709	0.697	0.714	0.710	0.703	0.990	0.999	0.991
26	0.697	0.712	0.689	0.698	0.714	0.709	0.998	0.998	0.973
27	0.684	0.693	0.680	0.685	0.694	0.683	0.999	0.998	0.996
2	0.680	0.692	0.684	0.681	0.693	0.687	0.999	0.998	0.995
4	0.676	0.672	0.666	0.680	0.674	0.671	0.995	0.998	0.993
28	0.676	0.685	0.666	0.690	0.702	0.684	0.980	0.976	0.973
1	0.667	0.683	0.666	0.671	0.685	0.684	0.994	0.996	0.973
14	0.666	0.666	0.665	0.666	0.666	0.666	1.000	1.000	0.998
16	0.666	0.697	0.699	0.666	0.698	0.709	1.000	0.998	0.985
32	0.666	0.666	0.665	0.667	0.666	0.668	1.000	1.000	0.996
33	0.666	0.696	0.665	0.668	0.700	0.674	0.998	0.993	0.987
30	0.264	0.266	0.274	0.264	0.266	0.274	1.000	1.000	1.000
7	0.203	0.214	0.211	0.203	0.214	0.211	1.000	1.000	1.000
15	0.059	0.059	0.061	0.059	0.059	0.061	1.000	1.000	1.000
Avg	*0.713*	*0.727*	*0.703*	*0.718*	*0.731*	*0.724*	*0.994*	*0.996*	*0.974*
Min	0.059	0.059	0.061	0.059	0.059	0.061	0.970	0.976	0.835
Max	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

If we consider the VRS results and compare them with the corresponding CRS results, we see that they are very similar. Even the efficient units of both returns to scale models are almost the same. In the VRS case, DO9 and DO22 are rated as fully efficient in the three seasons, just as DO8. The similarity of both returns to scale models appears clearly revising the last three columns of Table 3, where scale efficiency is reported. The average scale values for each season are always greater or equal to 0.974. Consequently, we can deal exclusively with the CRS model and forget the VRS model.

As said before, we will measure productivity resorting to the biennial Malmquist index. As it is well known, productivity is measured comparing the efficiency results for two consecutive time periods. Hence, we have obtained two productivity time indexes: one for the pair of seasons 2008-2009 and another for 2009-2010. Since only the CRS model needs to be considered, we have reported in Table 4 each biennial Malmquist index together with its decomposition into two factors: efficiency change and technological change. The biennial Malmquist requires the evaluation of all the units with respect to the corresponding biennial

Table 4. Biennial constant return to scale (CRS) scores and Malmquist indexes (2008-2009 and 2009-2010)

DO	Biennial Malmquist 208-2009					Biennal Malmquist 2009-2010				
	CRS_{2008}	CRS_{2009}	Efficiency change	Technological change	Malmquist	CRS_{2009}	CRS_{2010}	Efficiency change	Technological change	Malmquist
1	0.667	0.677	0.976	1.009	0.985	0.681	0.681	1.025	0.975	0.999
2	0.680	0.692	0.983	1.000	0.983	0.692	0.685	1.012	0.998	1.010
3	0.796	0.810	0.942	1.043	0.982	0.831	0.800	1.086	0.956	1.038
4	0.676	0.672	1.005	1.000	1.006	0.672	0.670	1.010	0.993	1.003
5	0.706	0.707	0.999	1.000	0.999	0.707	0.706	1.005	0.996	1.001
6	0.736	0.742	0.992	0.999	0.991	0.742	0.725	1.023	1.000	1.023
7	0.202	0.214	0.952	0.996	0.948	0.214	0.204	1.012	1.034	1.046
8	0.999	1.000	1.000	0.999	0.999	1.000	0.989	1.000	1.011	1.011
9	1.000	0.666	1.000	1.500	1.500	0.999	0.667	1.001	1.497	1.499
10	0.887	0.886	0.917	1.091	1.000	0.943	0.891	1.116	0.947	1.058
11	1.000	0.869	1.066	1.080	1.151	0.916	0.896	1.070	0.955	1.023
12	0.707	0.699	0.997	1.013	1.011	0.706	0.702	1.017	0.988	1.005
13	0.752	0.735	1.023	1.001	1.024	0.735	0.723	1.021	0.996	1.017
14	0.666	0.666	1.000	1.000	1.000	0.666	0.666	1.002	0.998	1.000
15	0.059	0.059	1.004	0.996	1.000	0.059	0.059	0.968	1.033	1.000
16	0.666	0.689	0.956	1.011	0.967	0.694	0.708	0.998	0.984	0.981
17	0.810	0.817	0.990	1.001	0.991	0.817	0.800	1.029	0.992	1.021
18	0.759	0.772	0.972	1.011	0.983	0.776	0.773	1.073	0.935	1.003
19	0.723	0.722	0.995	1.006	1.000	0.724	0.727	1.065	0.935	0.996
20	0.769	0.828	0.864	1.074	0.928	0.871	0.826	1.134	0.930	1.055
21	0.861	0.830	1.038	0.999	1.037	0.830	0.822	1.009	1.000	1.009
22	0.973	0.977	0.973	1.023	0.995	0.990	1.000	1.000	0.990	0.990
23	0.757	0.776	0.935	1.043	0.975	0.799	0.785	1.045	0.974	1.017
24	0.716	0.728	0.962	1.024	0.984	0.739	0.765	0.980	0.986	0.966
25	0.766	0.763	0.997	1.007	1.005	0.766	0.749	1.029	0.994	1.023
26	0.697	0.700	0.978	1.017	0.995	0.708	0.705	1.033	0.972	1.005
27	0.684	0.693	0.987	1.000	0.987	0.693	0.683	1.019	0.996	1.015
28	0.676	0.686	0.987	0.999	0.986	0.685	0.672	1.029	0.991	1.020
29	0.734	0.730	1.004	1.002	1.006	0.731	0.711	1.033	0.995	1.028
30	0.263	0.266	0.992	0.996	0.988	0.266	0.265	0.971	1.034	1.005
31	0.777	0.774	0.963	1.042	1.004	0.796	0.778	1.051	0.974	1.024
32	0.666	0.666	1.000	1.000	1.000	0.666	0.666	1.002	0.998	1.000
33	0.666	0.684	0.958	1.017	0.974	0.692	0.669	1.046	0.989	1.034
34	0.730	0.746	0.931	1.051	0.979	0.772	0.757	1.170	0.872	1.020
Avg	*0.712*	*0.704*	*0.981*	*1.031*	*1.011*	*0.723*	*0.704*	*1.035*	*0.992*	*1.027*
Min	0.059	0.059	0.864	0.996	0.928	0.059	0.059	0.968	0.872	0.966
Max	1.000	1.000	1.006	1,500	1.500	1.000	1.000	1.170	1.497	1.199

frontier. The results for all the units and the first two periods appear in columns 2 to 6 of Table 4, while the corresponding results for the last two periods appear in columns 7 to 11. As explained in M&M Section, the CRS biennial efficiency scores are evaluated for calculating the corresponding Malmquist indexes. If we consider the last row of Table 4, we find the corresponding average value for each column. The average biennial CRS efficiency scores have decreased in both comparisons, approximately 1% in the first biennium and 2% in the second. The same happens with the productivity, also declining in both comparisons. In fact, the average biennial Malmquist for the first two seasons is 1.011 while that corresponding to the second two seasons is 1.027. These two small productivity regresses are explained differently. In the first case, the average efficiency change slightly increases (0.981) while the average technological change slightly decreases (1.031). Exactly the opposite behavior happens in the second biennium: while the average efficiency change decreases slightly (1.035), the average technological change smoothly increases (0.992). Nonetheless, the changes are so small that what is really relevant is the almost uniform behavior of the DOs over the three considered seasons. If we revise the productivity indexes for the four DOs with better efficiency scores in the seasonal evaluation (DO8, DO22, DO11 and DO9, see Table 3), we appreciate different behavior. DO8 shows practically no productivity change in the first biennium and a slight regress in the second. Responsible for this change is the technological change. The second most efficient unit, DO22 shows a positive evolution in both bienniums. DO11, the third efficient unit, shows a decline in productivity throughout the seasons. DO9 presents the worst Malmquist values, with a deep decline due to its technological change. Finally, with respect to the three DOs with the lowest seasonal efficiency scores (DO15, DO7 and DO30), the worst one (DO15) remains without any productivity change, maintaining its low performance. Both DO7 and DO30 improve their productivity in the first transition but deteriorate in the second transition.

We may draw some additional economic conclusions by analyzing the efficiency scores obtained together with the basic economic features of the DOs under revision. First, we would like to point out that, although there is no statistically significant correlation between efficiency scores and year of recognition for the 34 DOs in any of the three seasons considered (Table 5), the four most efficient DOs are less than 25 years old. Moreover, two of the three less efficient DOs, DO15 and DO30, belong to the subgroup of oldest DOs, with 1932 as year of recognition (80 years old).

If we relate, in each year, the efficiency of the DOs with their surface we detect a statistically significant correlation (Table 5) so that the DOs with smaller sizes are more efficient. As mentioned earlier, the three biggest DOs are the least efficient ones while the most efficient units entail several small DOs. A similar conclusion holds when correlating the efficiency scores with the additional variable "number of vine growers in each DO". This negative correlation could be explained because fewer producers mean a larger average size of each farm and consequently, a potential better use of the productive resources.

Table 5. Pearson correlation among bounded adjusted measure (BAM) efficiency scores (CRS) and different variables

Variables	BAM efficiency scores (CRS)		
	2008	**2009**	**2010**
Year of recognition	0.260	0.295	0.251
Surface (size)	–0.720**	0.723**	–0.718**
Number of wine growers	–0.695**	–0.685**	–0.656**

** Correlation is significant at the 0.01 level (2-tailed).

How can we explain that the biggest DOs are also the most inefficient? Our suggestion is that the inefficient DOs earn a significant part of their benefits by selling bulk wine within the domestic market. This part of the benefits does not appear on the output side of our model because Spanish DOs are not allowed to sell bulk-wine as such.

One last comment is worth mentioning. The DOs that produce a kind of wine that is not the traditional red or white, such as sparkling wine or local white wine, have managed so as to obtain a successful market niche. In fact, DO8, efficient during the three periods, only commercializes 'Cava', a sparkling wine that only has famous French Champagnes as a competitor. Moreover, DO9 and DO11 commercialize almost only 'Chacolí' (99% of its total production), a local white wine from the Basque Region, and DO22 commercializes almost only 'Alvariño' (again, 99% of its total production), a local white wine from the Galicia Region. As said before, these are the four most efficient DOs in our analysis. The lack of domestic competition and the weak presence of foreign wines are the keys to success by these four DOs. On the other side, the three worst DOs produce mainly traditional red and white wines. In percentage of the total production, DO15 devotes 90% of its production to traditional wines (48% white and 42% red), DO7 89% (37% and 52%) and DO30 80% (14% and 66%).

Discussion

In this paper, we have resorted to the BAM measure because the input and output range bound restrictions are in accordance with the selection of our empirical dataset. Moreover, BAM offers us a balanced efficiency score, as explained in Cooper *et al.* (2011). Finally, and in order to capture the productivity regress or progress for our three-season database, without creating infeasibilities, we have resorted to the biennial Malmquist index.

Our DEA models have allowed us to classify the 34 Spanish DOs considered according to their efficiency scores in each of the three seasons. One of the main features of our dataset is that the average efficiency score for each season is quite high —over 0.70— and with small variations between seasons. We have also detected that DOs with large surfaces are the most inefficient ones. We have suggested that this explanation could be bulk sales in the domestic market. On the other hand, the small DOs always obtain good efficiency scores. Moreover, the results associated to the CRS and VRS models are very similar, meaning that there is practically no scale effect. For this reason, we have continued our analysis resorting only to the CRS model. This choice is compulsory if we want to estimate productivities (Lovell, 2003). In both biennia, the productivity decline is small but is explained in each biennium by a different factor. This can be interpreted as a steady behavior by the Spanish subset of 34 DOs. In the future, and when new data become available, the maturity of the quality wine sector in Spain can be checked again. Other interesting economic conclusions are: (i) in Spain, where foreign competition is weak, the most successful DOs are the ones that have specialized their production within a market niche such as "Cava", "Chacolí" and "Alvariño"; (ii) in each DO, less number of wine growers is associated to higher efficiencies scores, and (iii) there is no statistical significant relation between efficiency scores and year of recognition of the DO.

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