Animals' Health Control Efficiency in Northwest Portugal: A Two-stage DEA Approach

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A two-stage approach is employed to analyze the efficiency of cooperatives responsible for ruminants' disease control (OPP) at the farm level in Northwest Portugal. In the first stage, Data Envelopment Analysis (DEA) is used to estimate and decompose input-based overall inefficiency for each OPP. The input-based inefficiency measures are generated using the directional input distance function. In the second stage, the inefficiency estimates are regressed on environmental and organizational factors in order to explain efficiency differentials. Despite substantial environmental differences, the empirical results indicate that most cooperatives can reduce costs by improving scale efficiency and pure technical efficiency.

Keywords: input directional distance function, bootstrapping, economic efficiency, animal health services.

Introduction

Under the Obligatory Sanitary Program (OSP), ruminant´s disease control at the farm level in Northwest Portugal[1] is provided by 32 county-level farm Cooperatives, called *Organizações de Produtores Pecuários* (OPPs).

The OPPs were formed after Portugal became a member of the European Economic Community (E.E.C.) in 1986[27]. These cooperatives have been largely subsidized by the European Union (E.U.) and the Portuguese government to provide OSP services to farmers.

In 2001-2005, the amount of public support to the OSP in Northwest Portugal decreased 31% at nominal prices. For the period of 2005-2009, a further decrease of 57% was predicted [27]. The sharp decline in the subsidies to the OSP in the northwest region may be due to several reasons. The E.U. is presently concerned about the market distorting effects of control and eradication programs in several member states and proposals involving a cost-sharing scheme with farmer contributions have been considered[6,7,8]. In the last few years, the Portuguese government has cut public expenses dramatically in order to reduce its budget deficit as required by the E.U. Finally, ruminant herds have been decreasing in the northwest region of Portugal[2].

The structure and organization of the OSP services market are expected to change in the near future [27]. In 2005, each OPP operated in an exclusive county area, subject to the existing herds in the county and without competition from other suppliers. Prices charged for the OSP services and demand for OSP services vary across OPPs. The supply costs of OSP services also differ among OPPs, due mainly to environmental factors.[3] However, in the future, there will be free access to the OSP services market. Each OPP will probably face competition from other OPPs and other suppliers of OSP services.[4]

The changes in the structure of the OSP services market may have a large impact on the current organization of OPPs if substantial efficiency gains can be obtained from reorganization and from an increase in the competition among OPPs. Is it possible for the OPPs to reduce the costs of providing OSP services as well as other services? How can the OPPs improve efficiency? What is the impact of environmental and organizational factors on the efficiency of OPPs? This article aims at providing answers to these questions.

To answer the above questions and to investigate the efficiency performance of OPPs we have employed a two-stage approach. In the first stage, cost, allocative, scale, congestion, and pure technical inefficiency estimates are computed for each OPP using Data Envelopment Analysis (DEA). The input-based inefficiency measures used in this article are generated from the duality between the cost function and the

[1] In this article, Northwest Portugal corresponds to the former Entre Douro e Minho Agrarian Region.

[2]This reduction in the northwest region is due to farm and land abandonment and to increases in herd productivity. For instance, dairies, mostly located in the coastal counties of the region, have had an enormous increase in milk production per cow during the last few decades.

[3]Environmental factors are factors that are not under control of the OPPs but can influence their efficiency performance. It is easier to supply OSP services in some OPP areas than in others.

[4]The OPPs belong mostly to county-level cooperatives. These cooperatives form unions at the regional level to deal with ruminants' disease control (UCADESA) and to deal with milk collection (AGROS). For a variety of reasons, county-level cooperatives in the region seem to be more willing to cooperate among each other than to compete.

input directional distance function [3]. In the second stage, maximum likelihood is employed to regress the inefficiency estimates on environmental and organizational factors. The single bootstrap procedure proposed by Simar and Wilson [21] is used to build confidence intervals for regression coefficients.

The approach adopted takes into account the recent statistical criticisms of previous two-stage approaches and adopts the remedies provided by Simar and Wilson[21]. In addition, this article is most likely the first application of a DEA approach to analyze the performance of animal health services.

The article unfolds as follows. We present inefficiency measures using a directional input distance function in section 2 and in section 3 we discuss the two-stage approach to analyze inefficiency. This is followed by a description of the data in section 4 and of the empirical results in section 5. Section 6 concludes the article.

Inefficiency Measures

Directional distance functions are more general representations of production technology since they encompass as particular cases more conventional distance functions [3]. In contrast to radial distance functions, directional distance functions provide difference measures rather than ratio measures of relative efficiency and do not impose proportional variations in inputs or outputs. The directional representation of the production technology is also extremely useful in modeling production in the presence of input or output congestion and measuring performance accounting for inputs that obstruct production or bad outputs [11, 13].

Behavioral assumptions are not required for estimating technical inefficiency measures; but they are required for estimating economic inefficiency measures. The OPPs are county-level cooperatives. The OSP is the main service provided by each OPP and is exogenously determined. In this article, OPPs are assumed to be cost minimizing Decision Making Units (DMU). Thus, in our case the directional input distance function is an adequate representation of the technology. The input-based inefficiency measures employed in this article are generated using the directional input distance function proposed by Chambers, Chung, and Färe [3]. The directional input distance function is formally defined as

$$\vec{D}_I(y,x;g_x) = \sup_{\theta}\{\theta \in R : (x-\theta g_x) \in L(y)\}, \text{ if } (x-\theta g_x) \in L(y) \text{ for some } \theta,$$

$$\vec{D}_I(y,x;g_x) = -\infty, \text{ otherwise,} \tag{1}$$

where $L(y)$ is the input requirement set, $x \in R_+^N$ is a vector of inputs, $y \in R_+^M$ a vector of outputs and $g_x \in R_+^N$, $g_x \neq 0_N$, denotes a directional vector. The directional input distance function projects the input vector, in a pre-assigned direction, onto the input isoquant.

This direction can differ from the radial direction of the origin, implying the directional distance function is a more general representation of the production technology [4]. Since θg_x is subtracted from x, this function contracts inputs in the direction $(-g_x)$. If $x \in L(y)$, $\vec{D}(y,x;g_x) \geq 0$. $\vec{D}_I(y,x;g_x) < 0$ implies $x \notin L(y)$.

Chambers, Chung, and Färe [3] show that under strong disposability of inputs, the directional distance function is a complete representation of the production technology. Duality between the directional input distance function and the cost function allows an additive decomposition of cost inefficiency. Following Chambers, Chung, and Färe [3,4], cost inefficiency can be decomposed as follows:

$$\frac{w'x - C(y,w)}{w'g_x} = \vec{D}_I(y,x;g_x) + AIE \tag{2}$$

where $C(y,w)$ is the cost function, $\vec{D}_I\left(y,x;g_x\right)$ is the directional input distance function representing technical inefficiency and *AIE* is a residual component indicating allocative inefficiency. The left-hand side of (2) is the cost inefficiency measure. Cost inefficiency is measured by the difference between actual cost and minimum cost, normalized by the value of the directional vector.

In this article, the directional vector is the input vector i.e., $g_x = x$,[5] and input technical inefficiency is further decomposed into three components: pure technical inefficiency, congestion inefficiency and scale inefficiency. The decomposition of technical inefficiency proposed by Färe, Lovell and Grosskopf [14] is multiplicative since it is based on the Shephard input distance function. In contrast, the decomposition established in this article is additive. The additive decomposition of technical inefficiency is as follows

$$\vec{D}_I\left(y,x;x\,|\,C,S\right)=\vec{S}_I\left(y,x;x\,|\,S\right)+\vec{C}_I\left(y,x;x\,|\,V\right)+\vec{F}_I\left(y,x;x\,|\,V,W\right) \tag{3}$$

where *C* and *V* denote respectively constant and variable returns to scale, *S* and *W* indicate respectively strong and weak disposability of inputs, $\vec{S}_I\left(y,x;x\,|\,S\right)$ is the scale inefficiency measure, $\vec{C}_I\left(y,x;x\,|\,V\right)$ represents the congestion inefficiency measure and $\vec{F}_I\left(y,x;x\,|\,V,W\right)$ is the pure technical inefficiency measure.

The scale inefficiency measure is defined as

$$\vec{S}_I\left(y,x;x\,|\,S\right)=\vec{D}_I\left(y,x;x\,|\,C,S\right)-\vec{D}_I\left(y,x;x\,|\,V,S\right) \tag{4}$$

with $\vec{S}_I\left(y,x;x\,|\,S\right)\geq 0$. Note that $L(y|V,S)\subseteq L(y|C,S)$ [14]. If $\vec{S}_I\left(y,x;x\,|\,S\right)=0$, the firm is scale efficient, since it is equally technically inefficient relative to (*C*,*S*) and (*V*,*S*) technologies. $\vec{S}_I\left(y,x;x\,|\,S\right)>0$ indicates the firm is scale inefficient since it is more technically inefficient relative to technology (*C*,*S*) than to technology (*V*,*S*). The sources of scale inefficiency can be identified by comparing $\vec{D}_I\left(y,x;x\,|\,C,S\right)$ with $\vec{D}_I\left(y,x;x\,|\,N,S\right)$, where *N* denotes non-increasing returns to scale. If $\vec{D}_I\left(y,x;x\,|\,C,S\right)=\vec{D}_I\left(y,x;x\,|\,N,S\right)$, scale inefficiency is due to increasing returns to scale (IRS). $\vec{D}_I\left(y,x;x\,|\,C,S\right)>\vec{D}_I\left(y,x;x\,|\,N,S\right)$ indicates scale inefficiency is due to decreasing returns to scale (DRS).

The congestion inefficiency measure is given by

$$\vec{C}_I\left(y,x;x\,|\,V\right)=\vec{D}_I\left(y,x;x\,|\,V,S\right)-\vec{D}_I\left(y,x;x\,|\,V,W\right) \tag{5}$$

where $\vec{C}_I\left(y,x;x\,|\,V\right)\geq 0$. Note that $L(y|V,W)\subseteq L(y|V,S)$ [14]. If $\vec{C}_I\left(y,x;x\,|\,V\right)=0$, there is no input congestion inefficiency. $\vec{C}_I\left(y,x;x\,|\,V\right)>0$ indicates input congestion inefficiency.

The pure technical inefficiency is the input measure of technical inefficiency relative to a (*V*,*W*) technology; i.e.,

$$\vec{F}_I\left(y,x;x\,|\,V,W\right)=\vec{D}_I\left(y,x;x\,|\,V,W\right) \tag{6}$$

Given the additive decomposition of technical inefficiency in (3), the cost inefficiency measure is decomposed as follows

[5] With gx=x the directional vector is DMU specific and determined by each OPP input vector. In this case, the radial input distance function can be recovered from the directional input distance function [3]. Although it is possible to make a radial interpretation of our inefficiency measures, the choice of the observed input vector as the directional vector does not imply a radial inefficiency measure. Rather, the inefficiency measures employed in this study are still directional and the decompositions in (2) and (3) are additive as opposed to multiplicative decompositions that are based on radial distance functions.

$$\vec{O}_I\left(y,x,w;x\,|\,C,S\right)=S_I\left(y,x;g_x\,|\,S\right)+\vec{C}_I\left(y,x;g_x\,|V\right)+\vec{F}_I\left(y,x;g_x\,|V,W\right)+AIE \quad (7)$$

where $\vec{O}_I\left(y,x,w;x\,|\,C,S\right)=\dfrac{w'x-C(y,w)}{w'x}$. Given the cost inefficiency measure and the inefficiency measures in (4)-(6), *AIE* is determined residually.

The Empirical Model

The empirical model involves two stages. In the first stage, the inefficiency scores for each OPP are generated using DEA. In the second stage, a single bootstrap procedure is employed to investigate the impact of environmental and organizational factors on the inefficiency scores.

First Stage

The input-based inefficiency measures discussed in the previous section are computed using DEA. DEA is a non-parametric programming method that has been widely used in the evaluation of productive inefficiency [5,14,16,17] as well as environmental performance and productivity growth [12,14,26].

Consider a sample of *K* OPPs and let y^k and x^k be, respectively, the vector of observed outputs and inputs for OPP *k* and *w* the vector of input prices faced by all OPPs. To generate the cost inefficiency measure presented in the previous section, the minimum cost for each OPP *k*, *k*=1,…,*K*, is computed by running the following cost minimization problem

$$C(y^k,w)=\min_{x,\lambda^j}\left\{wx: y_m^k\le\sum_j\lambda^j y_m^j, m=1,...,M;\; x_n\ge\sum_j\lambda^j x_n^j, n=1,...,N;\; \lambda^j\ge 0,\, j=1,,,,K\right\} \quad (8)$$

where λ^j is the intensity variable of OPP *j*.
The decomposition of technical inefficiency in (3) requires running several linear mathematical programming problems. In particular, the inefficiency measures in (4)-(6) require generating measures of technical inefficiency relative to different production technologies. The measure of technical inefficiency relative to a (*C*,*S*) technology for OPP *k* is obtained by solving the following problem

$$\vec{D}_I(y^k,x^k;x^k\big|C,S)=\max_{\theta,\lambda^j}\left\{\theta: y_m^k\le\sum_j\lambda^j y_m^j, m=1,...,M;\; x_n^k(1-\theta)\ge\sum_j\lambda^j x_n^j, n=1,...,N;\lambda^j\ge 0,\, j=1,,,,K\right\} \quad (9)$$

The other measures of technical inefficiency are computed in a similar fashion. $\vec{D}_I\left(y,x;x\,|\,V,S\right)$ is computed as in (9) by adding the constraint $\sum_j\lambda^j=1$; $\vec{D}_I\left(y,x;x\,|\,N,S\right)$ is computed similarly by adding the constraint on the intensity variables $\sum_j\lambda^j\le 1$. The measure of technical inefficiency relative to a (*V*,*W*) technology is computed for each firm *k* as follows

$$\vec{D}_I(y^k, x^k; x^k | V, W) = \max_{\theta,\lambda^j} \left\{ \theta : y_m^k \le \sum_j \lambda^j y_m^j, m = 1,..., M; \right.$$
$$x_n^k(1-\theta) \ge \sum_j \lambda^j x_n^j,\ \ n = 1,..., N^\alpha;$$
$$x_n^k(1-\theta) = \sum_j \lambda^j x_n^j,\ \ n = N^\alpha + 1, N^\alpha + 2..., N; \quad (10)$$
$$\left. \sum_j \lambda^j = 1,\ \lambda^j \ge 0,\ j = 1,,, K \right\}$$

where N^α is the number of inputs that is strongly disposable and $(N - N^\alpha)$ is the number of inputs that is weakly disposable. Weak disposability is imposed by using the strict equality on the $(N - N^\alpha)$ input constraints.

Second Stage

The second stage involves an explanatory analysis of the inefficiency scores using environmental and organizational variables to account for exogenous factors that affect the efficiency performance of OPPs. Let $\hat{\delta}$ be a $K \times 1$ vector of inefficiency scores and Z be a $K \times r$-matrix of observations on r environmental and organizational factors. Following the traditional approach, a maximum likelihood regression model would be specified as follows:

$$\hat{\delta} = Z\beta + \varepsilon \ge 0 \quad (11)$$

where β is a $K \times 1$-vector of parameters.

Given the small size of the sample and the number of outputs and inputs considered in this study, the single bootstrap procedure is used.[6] The single bootstrap procedure is based on the following algorithm [21]:

[1] Use the $\hat{\delta}$ obtained in the first stage and run the maximum likelihood regression with left-truncation at zero in (11) to obtain an estimate $\hat{\beta}$ of β;

[2] Loop over the next three steps ([2.1.] a [2.3.]) L times to obtain a set of L bootstrap estimates $\hat{\beta}^*$ of β:

[2.1.] Draw ε from the $N(0, \hat{\sigma}_\varepsilon^2)$ distribution with left truncation at $(0 - Z\hat{\beta})$,[7]

[2.2.] Compute $\delta^* = Z\hat{\beta} + \varepsilon$,

[2.3.] Use de maximum likelihood method to estimate the truncated regression of δ^* on Z and get the estimates $\hat{\beta}^*$ of β.

[6] The results of the Monte Carlo experiments conducted by Simar and Wilson [21] for each algorithm (single and double bootstrap) indicate that, for small samples sizes and larger model dimensions, the root-mean–square-error of the parameter estimators and the variance estimator is lower when the single bootstrap algorithm is used.

[7] See the Appendix in Simar and Wilson [21] for details on how to draw from a left-truncated normal distribution.

[3] Order the L bootstrap estimates of each element in $\hat{\beta}^*$ obtained in [2] and construct a $(1-\alpha)$ confidence interval.

Data

Cross sectional data from the year 2005 of 32 OPP are available for this research.[8] The data set contains money values and (occasionally) prices and quantities of OPP field and office activities that are carried out under the OSP, as well as other activities. The data also contains information on environmental and organizational factors affecting the efficiency of operation of each OPP. Besides the limitations and remedies we discussed in the previous section for the second stage regressions, the very small sample size can also be a challenge for DEA in the first stage. Measurement error in the data could shift the DEA estimated frontier and would change the DMUs inefficiency scores.[9]

First Stage Data

For the first stage of our analysis we distinguished two outputs and three inputs. Outputs are services provided under the OSP (y_1) and other services (y_2).[10] Inputs are consumables (x_1), labor (x_2) and capital (x_3). The quantity y_1 is measured in equivalent bovines[11] and the quantity of (y_2) is reflected by its monetary value in 2005 prices, thereby ensuring that quality differences between OPPs are reflected in the quantity [9]. The quantity of consumables (x_1) is measured in monetary value of 2005 and its price w_1 is assumed to be unity. The quantity of labor (x_2) is measured in equivalent auxiliary technician labor and its price w_2 is measured as the average sample wage of this type of worker.[12] Finally, we constructed a quality corrected measure of the annual cost of capital to reflect the quantity of capital (x_3). The quality corrected measure was obtained by dividing the observed inventory value of capital by the average ratio of observed inventory value and observed annual costs. Prior to estimation, all prices and quantities have been normalized, i.e., they have been divided by their respective averages. In the Appendix, Table A1 presents the observed prices and quantities before normalization.

Second Stage Data

In the 2006 survey conducted among the OPP, several factors not under control of the OPP have been identified by the veterinaries as having significant influence on the performance of each OPP providing the OSP. The factors are: 1) the number of animal heads per farm, 2) the distance of the OPP headquarters to the farms, 3) farms' dispersion, 4) the system of keeping the animals on the farms, and 5) people on the farms helping the OPP team containing the animals [27]. According to the veterinaries' field experience, the number of animal heads per farm (factor 1) increases the OPP efficiency of providing OSP services because the number of farmers to be contacted is smaller and the time per animal head necessary to provide the OSP is reduced. Distance of the OPP to the farms and dispersion of the farms (factors 2 and

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[8] A onetime survey was conducted of the 32 OPP in 2006 [27]. The available data set has 32 corresponding lines of observations.

[9] The practitioner rule for DEA suggests the need for 100 observations for each dimension. According to this rule, our sample size falls below reasonable thresholds. However, the rule is interpreted in the literature as a desideratum rather than a necessary condition. In what concerns measurement error, data collection and screening have been supervised by one of the authors. Therefore, we are confident that measurement error is not a major problem in our data.

[10] Examples of these other services are animal identification and control of existences, animal passports, animal hygiene, animal vaccination and other health services not included in the OSP, etc.

[11] Five small ruminants or one bovine correspond to one equivalent bovine.

[12] There are three types of workers in the OPP: veterinarians, auxiliary technicians, and administrative workers. We have considered the average wage of the auxiliary technicians and divided the cost of labor of each OPP by this wage to compute x_2.

3) increase the time it takes to provide the OSP, i.e. travel costs and time spent by the OPP team increase. The system of keeping the animals (factor 4) varies, between dairy and beef farms. According to the veterinaries, it is less complicated to provide the OSP to dairy farms rather than to beef farms. Finally, the presence of people on the farms helping to contain the animals (factor 5) reduces the time spent by an OPP team providing the OSP.

In the second stage model, the first factor is the number of equivalent bovines per farm (*Nebf)*. The number of kilometers traveled per farm (*Nkmf*) represents the second and third factors mentioned before. The fourth factor is reflected in two explanatory variables: the percentage of dairy farms (*Pdairy*) and the percentage of beef farms (*Pbeef*). The fifth factor is measured by *Age*, reflecting the percentage of farmers 50 years of age or older. The age of the farmers is likely to be an important variable explaining inefficiency differences since older farmers tend to help more containing the animals on the farms than younger farmers do. On average, older farmers have smaller farms, produce beef instead of milk, and are located in the mountainous areas of the Region. Additionally, we have included two environmental factors: *Psr,* the percentage of small ruminants on total ruminants, both measured in equivalent bovines, and *Nfarm,* the number of farms. Furthermore, we have also considered some organizational factors of each OPP such as *Ystr* (a dummy variable indicating the output structure), *Plfw* (percentage of total OPP labor allocated to field work), and *Opptype* (a dummy variable indicating whether the OPP belongs to a Cooperative). Table A2, in the Appendix, provides the descriptive statistics of the variables used in the second stage regression.

Empirical Results

The following abbreviations are used in this section: $\vec{O}_I = \vec{O}_I\left(y, x, w; x \mid C, S\right)$, $\vec{A}_I = AIE$, $\vec{C}_I = \vec{C}_I\left(y, x; x \mid V\right)$, $\vec{S}_I = \vec{S}_I\left(y, x; x \mid S\right)$, and $\vec{F}_I = \vec{F}_I\left(y, x; x \mid V, W\right)$.

First Stage Results

Table 1 shows first stage inefficiency estimates. Only two out of the thirty two OPPs are efficient overall (11 and 22); most of the OPPs present some source of inefficiency. Although for a few OPPs allocative and input congestion are important sources of inefficiency, for most OPPs scale inefficiency and pure technical inefficiency are the major components of overall inefficiency.

Table 1. First Stage Inefficiency Results

OPP ID #	$\vec{O}_I$	$\vec{A}_I$	$\vec{S}_I$	$\vec{C}_I$	$\vec{F}_I$	Returns to Scale
1	0,644	0,180	0,464	0,000	0,000	IRS
2	0,668	0,019	0,453	0,000	0,196	IRS
3	0,608	0,105	0,503	0,000	0,000	IRS
4	0,702	0,032	0,199	0,000	0,471	IRS
5	0,615	0,078	0,537	0,000	0,000	IRS
6	0,801	0,060	0,448	0,000	0,293	IRS
7	0,786	0,013	0,479	0,294	0,000	IRS
8	0,786	0,059	0,335	0,000	0,392	IRS
9	0,677	0,041	0,113	0,000	0,523	IRS
10	0,332	0,224	0,108	0,000	0,000	IRS
11	0,000	0,000	0,000	0,000	0,000	CRS
12	0,717	0,067	0,111	0,212	0,327	IRS
13	0,595	0,049	0,134	0,412	0,000	IRS
14	0,417	0,071	0,227	0,010	0,109	IRS
15	0,051	0,051	0,000	0,000	0,000	CRS
16	0,657	0,080	0,577	0,000	0,000	IRS
17	0,621	0,029	0,190	0,000	0,402	IRS

18	0,592	0,059	0,170	0,000	0,363	IRS
19	0,770	0,053	0,089	0,000	0,628	IRS
20	0,697	0,032	0,196	0,031	0,438	IRS
21	0,423	0,064	0,148	0,000	0,211	IRS
22	0,000	0,000	0,000	0,000	0,000	CRS
23	0,620	0,252	0,368	0,000	0,000	DRS
24	0,780	0,030	0,521	0,000	0,229	IRS
25	0,671	0,081	0,099	0,011	0,480	IRS
26	0,792	0,037	0,219	0,054	0,482	IRS
27	0,777	0,109	0,668	0,000	0,000	IRS
28	0,295	0,118	0,085	0,092	0,000	IRS
29	0,602	0,036	0,183	0,000	0,383	IRS
30	0,765	0,104	0,231	0,430	0,000	IRS
31	0,585	0,055	0,125	0,405	0,000	IRS
32	0,687	0,033	0,403	0,086	0,165	IRS
Mean	0,585	0,069	0,262	0,064	0,190	
Stdev	0,225	0,058	0,189	0,132	0,208	

Of the thirty two OPPs three are scale efficient and thus present Constant Returns to Scale (CRS). One OPP is characterized by Decreasing Returns to Scale (DRS) and the remaining twenty eight show Increasing Returns to Scale (IRS). Therefore, the result suggests that the vast majority of the OPPs (88%) could improve efficiency by increasing the scale of operation. The only way for an OPP to expand the size of the operation is by moving outside its own county area, into other OPP areas. That is, for some OPPs to grow others need to disappear and/or some type of merging agreement must be implemented.

Pure technical inefficiency is an important source of inefficiency for seventeen out of the thirty two OPPs. This result suggests that many OPPs will possibly have a substantial scope for improving efficiency of providing OSP services. OPPs may improve their own performance for example by exchanging information with other OPPs.[13]

Only two out of the thirty two OPPs are allocatively efficient. However, allocative inefficiency is a relevant source of inefficiency for only seven OPPs and it is particularly important for two OPPs (10 and 23). This means that these OPPs can substantially reduce their costs by choosing a mix of inputs that takes into account the input prices, i.e. reduce the use of expensive inputs and increase the use of cheap inputs.

Congestion inefficiency appears in eleven out of thirty two OPPs and is particularly relevant in five OPPs (7, 12, 13, 30, and 31). Congestion inefficiency is caused by the difficulty that OPPs face in adjusting the quantity of inputs.[14] The sources of input congestion are investigated by running the (V,W) model in (10) (see Table A3 in the Appendix). In some OPPs congestion inefficiency is combined in all inputs. In others, congestion is confined to a single input. The result that congestion is present in all inputs suggests that several OPPs face managerial or organizational problems that inhibit them from adjusting the use of inputs. Managerial problems may arise from a lack of incentives among the management to adjust (inertia); organizational problems may arise from the presence of fixed contracts that limit the flexibility of the use of inputs.

Second Stage Results

We built 95% and 80% Bootstrap Confidence Intervals using L=2000 replications as suggested by Simar and Wilson [21]. Simar and Wilson [21] point out that the higher the confidence level, the higher the difference between the real and the nominal confidence levels. This is the reason we built 80%

[13] According to UCADESA [27], presently each OPP operates as if the other didn't exist. UCADESA hasn't promoted this type of exchange yet.

[14] There has been a quick decline of farms and herds and thus of services provided under the OSP for some OPPs in the Region [27]. These OPPs may experience difficulties in a corresponding reduction of inputs.

Confidence Intervals. Table 2 shows second stage beta coefficients and Bootstrap Confidence Intervals for all the inefficiency estimates except congestion, for which estimation was not possible.[15] A parameter estimate is significant when the value of zero is not within the confidence interval.[16]

Table 2. Second Stage Coefficients and Bootstrap Confidence Intervals

$\vec{O}_I$	**Coefficient**	**BSCI, 5%**	**BSCI, 20%**
Constant	1,115*	[0,702;1,564]	[0,835;1,393]
Nebf	-0,221*	[-0,314;-0,132]	[-0,284;-0,161]
Nkmf	0,010	[-0,695;0,089]	[-0,042;0,062]
Pdairy	0,096**	[-0,042;0,225]	[0,008;0,182]
Pbeef	0,142	[-0,335;0,617]	[-0,175;0,439]
OPPtype	0,041	[-0,078;0,165]	[-0,039;0,121]
Ystr	-0,035	[-0,129;0,062]	[-0,098;0,029]
Plfw	-0,122	[-0,431;0,193]	[-0,328;0,084]
Age	-0,325**	[-0,724;0,081]	[-0,586;-0,078]
Psr	0,377**	[-0,115;0,081]	[0,075;0,687]
Nfarm	-0,126*	[-0,195;-0,055]	[-0,173;-0,079]
$\vec{A}_I$	**Coefficient**	**BSCI, 5%**	**BSCI, 20%**
Constant	0,090	[-0,207;0,382]	[-0,095;0,272]
Nebf	0,044**	[-0,017;0,103]	[0,000; 0,078]
Nkmf	-0,019	[-0,082;0,035]	[-0,057;0,016]
Pdairy	-0,098**	[-0,195;0,008]	[-0,152;-0,021]
Pbeef	-0,264**	[-0,777;0,092]	[-0,540;-0,022]
OPPtype	-0,028	[-0,126;0,070]	[-0,085;0,038]
Ystr	0,066**	[-0,011;0,142]	[0,013;0,106]
Plfw	-0,074	[-0,288;0,151]	[-0,204;0,068]
Age	0,140	[-0,125;0,413]	[-0,041;0,305]
Psr	-0,349**	[-0,738;0,008]	[-0,568;-0,081]
Nfarm	-0,042**	[-0,100;0,014]	[-0,074;-0,004]
$\vec{S}_I$	**Coefficient**	**BSCI, 5%**	**BSCI, 20%**
Constant	0,742*	[0,065;1,419]	[0,286;1,159]
Nebf	-0,062	[-0,222;0,092]	[-0,166;0,045]
Nkmf	-0,054	[-0,198;0,067]	[-0,142;0,026]
Pdairy	-0,231*	[-0,444;-0,005]	[-0,354;-0,071]
Pbeef	0,129	[-0,603;0,825]	[-0,358;0,566]
OPPtype	-0,087	[-0,261;0,109]	[-0,200;0,043]
Ystr	0,101	[-0,067;0,253]	[-0,015;0,190]
Plfw	-0,499**	[-0,992;0,039]	[-0,791;-0,144]
Age	0,360	[-0,267;0,988]	[-0,066;0,715]
Psr	-0,093	[-0,891;0,613]	[-0,567;0,402]
Nfarm	-0,253*	[-0,395;-0,111]	[-0,328;-0,155]
$\vec{F}_I$	**Coefficient**	**BSCI, 5%**	**BSCI, 20%**
Constant	0,450	[-0,592;1,539]	[-0,192;1,107]
Nebf	-0,260*	[-0,547;-0,005]	[-0,403;-0,076]
Nkmf	0,069	[-0,128;0,242]	[-0,056;0,175]
Pdairy	0,133	[-0,180;0,438]	[-0,066;0,325]
Pbeef	-0,228	[-1,618;0,829]	[-1,076;0,424]

[15] For twenty one out of the thirty two OPPs congestion inefficiency is zero (Table 1). Thus, we lack degrees of freedom to run the truncated regression for congestion inefficiency estimates.

[16] Table A4 in the Appendix yields some diagnostic statistics for the second-stage regressions. The assumed model is questionable only for the allocative inefficiency estimates.

OPPtype	0,077	[-0,198;0,362]	[-0,106;0,246]
Ystr	-0,015	[-0,237;0,216]	[-0,154;0,133]
Plfw	-0,331	[-1,084;0,470]	[-0,791;0,194]
Age	0,035	[-0,947;1,030]	[-0,577;0,598]
Psr	-0,134	[-1,470;0,891]	[-0,898;0,573]
Nfarm	0,045	[-0,128;0,210]	[-0,070;0,147]

Significance at the 5% level is indicated by a star and at the 20% level is indicated by two stars.

Overall inefficiency is affected negatively and significantly by *Nebf* (the number of equivalent bovines per farm), *Age* (the percentage of farmers over 50 years or age), and *Nfarm* (the number of farms), and positively and significantly by *Psr* (the percentage of small ruminants on total ruminants in equivalent bovines). The effects are in accordance with the prior expectations of the veterinaries, i.e. transaction costs and time spent with the OSP diminish with *Nebf*. Although associated with smaller and more traditional farms producing beef, sheep, or goats and usually located in mountainous areas, older farmers offer more help to the OPP teams in handling the animals than younger farmers do. The efficiency of the OPPs increases with scale. Finally, OPPs dealing with sheep and goat farms are less efficient overall.

Allocative inefficiency is affected negatively by *Pdairy* (the percentage of dairy farms), *Pbeef* (the percentage of beef farms), *Psr* and *Nfarm* and most positively by *Nebf* and *Ystr* (a dummy variable indicating output structure). The results indicate that the OPPs dealing with more specialized farms and/or herds succeed more in choosing a mix of inputs that minimizes costs at given input prices than other OPPs. The results also indicate that the OPPs dealing with larger farms and the OPPs developing other services besides the OSP are less successful in making cost effective choices of input bundles. The latter result concerning output structure deserves a careful interpretation. Some OPPs in the Region are facing a quick decline of farms and herds and, thus, of the services they provide under the OSP. Because inputs lag declining, these OPPs are becoming more and more inefficient. A strategy they follow to reduce their inefficiency is to allocate inputs to the development of other services besides the OSP. This strategy is well documented in UCADESA [27]. Thus, these OPPs are not more inefficient because they develop other services. On the contrary, these OPPs would be even more inefficient if they were not developing these other services.

Scale inefficiency is affected negatively and significantly by *Pdairy*, *Plfw* (the percentage of labor allocated to field work) and *Nfarm*. The results suggest that the OPPs with a larger percentage of dairy farms operate on a more optimal (higher) scale. Dairy farms are located in the coastal counties of the region where OPPs are characterized by a larger scale of operation. They also suggest that the OPPs that operate on a larger scale allocate more labor to field work and thus less labor to administrative work. Finally, the results on *Nfarm* indicate that scale efficiency of the OPPs increases with scale of operation.

Pure technical inefficiency is affected negatively and significantly only by *Nebf*. The result is in line with the prior expectation expressed by the veterinaries. By sorting the OPPs from the lowest to the highest value of *Nebf*, one takes that OPPs with similar values for *Nebf* can have significantly different values for pure technical inefficiency. That is, although *Nebf* appears to be an important source of variability for pure technical inefficiency, there is scope for pure technical inefficiency improvements by the OPPs.

In order to determine the relative importance of environmental and organizational factors, we have computed the amount of variability of inefficiency that could be explained by the variability of these factors. The computations show that *Nebf* is the most important source of variability for overall inefficiency, followed by *Nfarm, Age, Psr*, and *Pdairy*. The variabilities of *Nebf* and *Psr* are the main sources in approximately equal shares for the variability of allocative inefficiency, followed by *Pdairy, Pbeef, Ystr*, and *Nfarm*, the latter also in approximately equal shares. *Nfarm* is the most important source of variability for scale inefficiency followed by *Pdairy* and *Plfw*. *Nebf* variability is the only (environmental) factor source of variability for pure technical inefficiency. We conclude that *Nebf* and *Nfarm* are the major (environmental) factors influencing the efficiency performance of the OPPs.

Potential Gains from Mergers

OPPs 2, 3, 5, 6 and 8 are presently in a process of merging. In order to measure the potential gains from merging, the pooled OPP inefficiency scores are computed from the DEA estimated frontier [2]. Table 3 provides the results.[17]

Table 3. Potential gains from merging OPPs

OPP ID #	$\vec{O}_I$	$\vec{A}_I$	$\vec{S}_I$	$\vec{C}_I$	$\vec{F}_I$	***Nebf***	***Nfarm***
2	0,668	0,019	0,453	0,000	0,196	6.95	549
3	0,608	0,105	0,503	0,000	0,000	6.76	517
5	0,615	0,078	0,537	0,000	0,000	7.38	445
6	0,801	0,060	0,448	0,000	0,293	5.87	476
8	0,786	0,059	0,335	0,000	0,392	6.78	464
Pooled	0,715	0,045	0,018	0,063	0,589	6,75	2451

Although the pooled OPP still presents increasing returns to scale, scale inefficiency decreases substantially. Mergers with similar values for *Nebf* have significantly different values for pure technical inefficiency. Thus, there is scope for pure technical efficiency improvements by these OPPs. The large increase of pure technical inefficiency for the pooled OPP is a consequence of returns to scale. That is, the same amount of outputs can be produced with fewer inputs.

Conclusions

A two-stage approach is employed to analyze the efficiency performance of cooperatives (OPPs) responsible for ruminants' disease control at the farm level in the Northwest region of Portugal.

Our first-stage results indicate that most of the OPPs present some source of inefficiency, namely scale inefficiency (increasing returns to scale) and pure technical inefficiency. Thus, it is possible for the OPPs to reduce the unit cost of providing the OSP services as well as the other services by removing these inefficiencies. For some OPPs to grow in scale others need to disappear and/or some type of merging agreement must be implemented. The potential efficiency gain for a group of five OPPs that is currently in a process of merging was investigated. Scale efficiency largely improves although returns to scale are not totally exhausted. In addition, due to returns to scale the same amount of outputs can be produced with fewer inputs. The empirical results also indicate that there is scope for improving on pure technical efficiency by exchanging information across OPPs.

Our second stage results suggest the influence of environmental and organizational factors on the efficiency performance of the OPPs. The number of equivalent bovines per farm (*Nebf*)) and the number of farms (*Nfarm*) have been identified as the major factors influencing the efficiency performance of the OPPs. *Nebf* is directly connected with the evolution of the agricultural sector and tends to increase over time with modernization and the inherent increase of farms' scale of operation.

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Appendix

Table A1. Observed Prices and Quantities

OPP ID #	Quantities					Prices				
	y_1	y_2	x_1	x_2	x_3	p_1	p_2	w_1	w_2	w_3
1	3864.00	0.00	8393.50	4.07	30405.15	18.21	1.00	1.00	10394.45	0.11
2	3814.00	0.00	11411.76	6.21	20472.35	19.71	1.00	1.00	10394.45	0.11
3	3492.40	0.00	7486.62	6.14	11881.83	20.04	1.00	1.00	10394.45	0.11
4	5845.00	0.00	30179.29	8.24	34737.54	20.47	1.00	1.00	10394.45	0.11
5	3282.80	5000.00	8503.29	4.15	20472.35	19.08	1.00	1.00	10394.45	0.11
6	2795.20	0.00	25475.97	3.98	30405.15	16.29	1.00	1.00	10394.45	0.11
7	3340.00	100.00	37194.23	4.88	21814.62	17.21	1.00	1.00	10394.45	0.11
8	3145.20	9164.71	27129.00	4.92	38995.68	20.17	1.00	1.00	10394.45	0.11
9	8589.60	0.00	39451.00	11.28	49382.45	20.33	1.00	1.00	10394.45	0.11
10	6166.60	12666.00	19725.85	2.50	21814.62	15.50	1.00	1.00	10394.45	0.11
11	5260.00	146214.85	11131.81	5.14	30326.61	14.77	1.00	1.00	10394.45	0.11
12	9874.60	0.00	88880.49	8.89	51765.80	17.30	1.00	1.00	10394.45	0.11
13	10400.00	0.00	39543.62	13.28	34737.54	17.15	1.00	1.00	10394.45	0.11
14	8080.00	15176.90	28694.38	6.30	21814.62	17.55	1.00	1.00	10394.45	0.11
15	32100.00	0.00	83640.00	10.20	46165.39	9.93	1.00	1.00	10394.45	0.11
16	2481.40	9211.50	14390.25	3.98	11881.83	18.77	1.00	1.00	10394.45	0.11
17	6905.60	6615.81	27701.20	8.46	33242.48	14.46	1.00	1.00	10394.45	0.11
18	8076.80	8120.00	22284.00	9.67	43175.28	21.10	1.00	1.00	10394.45	0.11
19	7173.80	0.00	47753.66	11.00	64989.90	21.59	1.00	1.00	10394.45	0.11
20	6548.00	8422.10	47763.80	8.71	31900.21	16.72	1.00	1.00	10394.45	0.11
21	10635.00	0.00	37202.24	6.31	30405.15	16.39	1.00	1.00	10394.45	0.11
22	50369.00	0.00	52295.36	29.32	79486.41	12.44	1.00	1.00	10394.45	0.11
23	19707.40	189854.10	211952.00	16.97	104651.24	12.96	1.00	1.00	10394.45	0.11
24	2593.80	0.00	15967.00	5.05	21814.62	24.81	1.00	1.00	10394.45	0.11
25	9560.80	0.00	34626.47	11.85	64767.26	18.87	1.00	1.00	10394.45	0.11
26	3233.80	34014.60	46978.98	7.73	40791.92	27.95	1.00	1.00	10394.45	0.11
27	2618.40	0.00	28398.00	2.53	21814.62	21.88	1.00	1.00	10394.45	0.11
28	16940.20	0.00	27324.61	10.96	48928.48	11.35	1.00	1.00	10394.45	0.11
29	6568.00	30000.00	18300.00	9.91	43175.28	15.23	1.00	1.00	10394.45	0.11
30	4270.00	5500.00	18000.00	6.76	51765.80	27.28	1.00	1.00	10394.45	0.11
31	10425.60	9928.20	28348.67	15.76	37728.98	21.97	1.00	1.00	10394.45	0.11
32	3597.60	15646.66	29307.70	4.41	23309.68	17.40	1.00	1.00	10394.45	0.11
Mean	8804.83	15801.11	36732.34	8.42	38094.40	18.28	1.00	1.00	10394.45	0.11

Stdev	9693.50	41203.53	37154.62	5.27	19823.98	4.10	0.00	0.00	0.00	0.00

Source: OPP Survey

Table A2. Observed Environmental and Organizational Factors

OPP ID #	Environmental and Organizational Factors									
	Nebf	Nkmf	Pdairy	Pbeef	OPPtype	Ystr	Plfw	Age	Psr	Nfarm
1	7.70	39.84	0.56	0.00	1	0	0.31	99.00	0.02	502
2	6.95	91.07	0.50	0.49	0	0	0.53	85.00	0.03	549
3	6.76	48.36	0.03	0.01	1	0	0.58	90.00	0.04	517
4	8.12	82.85	0.97	0.01	1	0	0.37	80.00	0.02	720
5	7.38	38.20	0.91	0.00	1	1	0.46	80.00	0.03	445
6	5.87	25.21	0.73	0.01	0	0	0.48	80.00	0.09	476
7	3.73	25.67	0.99	0.00	1	1	0.33	90.00	0.16	896
8	6.78	37.86	0.51	0.32	1	1	0.51	60.00	0.05	464
9	4.12	33.59	0.95	0.00	1	0	0.58	90.00	0.17	2084
10	21.26	68.97	0.81	0.06	1	1	0.95	80.00	0.01	290
11	17.65	25.17	0.58	0.08	1	1	0.44	85.00	0.01	298
12	5.05	9.47	0.59	0.00	1	0	0.51	75.00	0.13	1954
13	7.64	33.04	0.04	0.01	0	0	0.38	55.00	0.25	1362
14	10.77	20.00	0.33	0.02	1	1	0.58	80.00	0.01	750
15	50.79	109.88	1.00	0.00	1	0	0.56	20.00	0.00	632
16	5.36	43.20	0.05	0.00	1	1	0.69	80.00	0.17	463
17	3.64	39.41	0.91	0.00	0	1	0.57	99.00	0.44	1896
18	4.13	13.81	0.98	0.02	1	1	0.51	70.00	0.08	1955
19	4.61	23.67	0.32	0.00	1	0	0.51	85.00	0.16	1555
20	6.04	46.13	0.63	0.00	1	1	0.42	70.00	0.24	1084
21	15.13	19.20	0.88	0.01	1	0	0.50	70.00	0.02	703
22	17.86	34.74	0.26	0.00	1	0	0.50	60.00	0.00	2820
23	19.36	46.52	0.59	0.04	1	1	0.33	45.00	0.01	1018
24	3.32	8.31	0.05	0.00	1	0	0.35	74.87	0.51	782
25	6.83	115.22	0.07	0.01	1	0	0.50	70.00	0.07	1400
26	2.71	22.97	0.97	0.00	0	1	0.52	80.00	0.33	1193
27	1.73	11.30	0.10	0.00	0	0	0.47	90.00	0.27	1513
28	42.46	50.13	0.97	0.03	1	0	0.43	10.00	0.00	399
29	3.61	16.49	0.97	0.00	0	1	0.51	90.00	0.27	1819
30	4.74	18.89	0.50	0.00	1	1	0.74	98.00	0.20	900
31	3.23	10.83	0.01	0.12	1	1	0.35	80.00	0.26	3232
32	4.44	61.73	0.06	0.22	1	1	0.90	75.00	0.11	810
Mean	9.99	39.74	0.56	0.05			0.51	74.87	0.13	1109
Stdev	10.94	27.83	0.37	0.11			0.15	20.00	0.13	740

Source: OPP Survey

Table A3. Sources of Input Congestion

OPP ID #	Combined	x_1	x_2	x_3
1	0,000	0,000	0,000	0,000
2	0,000	0,000	0,000	0,000
3	0,000	0,000	0,000	0,000
4	0,000	0,000	0,000	0,000
5	0,000	0,000	0,000	0,000
6	0,000	0,000	0,000	0,000
7	0,294	0,294	0,000	0,000
8	0,000	0,000	0,000	0,000
9	0,000	0,000	0,000	0,000
10	0,000	0,000	0,000	0,000
11	0,000	0,000	0,000	0,000
12	0,212	0,212	0,000	0,000
13	0,412	0,000	0,006	0,000
14	0,010	0,001	0,000	0,000
15	0,000	0,000	0,000	0,000
16	0,000	0,000	0,000	0,000
17	0,000	0,000	0,000	0,000
18	0,000	0,000	0,000	0,000
19	0,000	0,000	0,000	0,000
20	0,031	0,031	0,000	0,000
21	0,000	0,000	0,000	0,000
22	0,000	0,000	0,000	0,000
23	0,000	0,000	0,000	0,000
24	0,000	0,000	0,000	0,000
25	0,011	0,000	0,000	0,011
26	0,054	0,054	0,000	0,000
27	0,000	0,000	0,000	0,000
28	0,092	0,000	0,000	0,092
29	0,000	0,000	0,000	0,000
30	0,430	0,000	0,000	0,430
31	0,405	0,000	0,405	0,000
32	0,086	0,086	0,000	0,000
Mean	0,064	0,021	0,013	0,017
Stdev	0,132	0,064	0,072	0,077

Table A4. Second Stage Truncated Regressions Descriptive Statistics

	Lower Limit	**Upper limit**	**Log likelihood**	**# of observations**	**Wald chi2(10)**	**Prob > chi2**
$\vec{O}_I$	0	+inf	33,363511	31	107,79	0,0000
$\vec{A}_I$	0	+inf	58,67883	31	8,42	0,5877
$\vec{S}_I$	0	+inf	26,929811	29	31,68	0,0005
$\vec{F}_I$	0	+inf	17.597989	17	24,96	0,0054