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Assessing the effects of managerial and production practices on the efficiency of commercial pig farming

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Abstract

A non-parametric data envelopment analysis (DEA) technique was applied to investigate the degree of technical and scale efficiency of commercial pig farming in Greece. Mean pure technical efficiency in a DEA model in which all variables were normalized with the number of sows was 0.83, indicating that there is ample potential for more efficient input utilisation in domestic pig farming. The normalized measurement of variables captures the fact that most scale-inefficient farms are operating under decreasing returns to scale. This implies that even smaller farms have expanded to a size larger than is optimal relative to the number of sows in their herds. In an attempt to explain variation in efficiency scores, the study focuses on certain managerial and breeding practices often not accounted for. Tobit analysis reveals that the choice of insemination method, origin of the genotype, and the feedstuff preparation system,

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as well as the mortality rate of piglets and the size class, have a significant impact on the efficiency level of pig farms.

Keywords: DEA; Frontier production function; Efficiency; Best practice; Managerial practices; Pig farming

1. Introduction

In livestock production, management practices can be defined as a set of alternative production techniques such as breeding and nutrition systems, genetics, feeds and feeding programmes, housing conditions, and animal health (Whittemore, 1993). Researchers in technical sciences are particularly interested in the optimal feeding ratio (i.e., composition of ingredients, percentage of vitamins and micronutrients, etc.), the origin of the genetic material (genotypes provided from breeding stock or from finishers), and the insemination method, as ways of improving the herd's quality characteristics.

These factors, however, apart from their technical interest, may have a crucial impact on the performance of a farm from an economic point of view as well. Today, the complexity of livestock production systems in a rapidly changing environment is widely recognised. With the increasing consciousness about excess production and the induced burden on the Common Agricultural Policy (CAP) budget, the main point of concern for the industry, as well as for EU officials and the academics, has shifted from output growth to efficient farm management.

Within this context, several researchers have focused on combining managerial and economic approaches with animal science (see, for instance, Rougoor et al., 1997; Tauer and Stefanides, 1998; Rougoor et al., 2000; Sorensen and Ostergaard, 2003). Over the last few years, performance analysis of decision entities has been given considerable attention, based on the realisation that comparable firms, operating under similar constraints and circumstances and producing similar outputs, exhibit wide variations in their competence. Economic theory asserts that the goal for efficient management is the optimal utilisation of inputs to produce outputs in such a manner that maximises economic returns. Based on Farrell's innovative article (1957), several approaches to efficiency and productivity assessment have been developed that can be classified into two broad categories: parametric and non-parametric frontier models. The former rely on the specification of an ad hoc functional form, impose certain a priori restrictions on the production technology, and estimate the parameters of the production or the cost function statistically. Alternatively, the latter construct a linear piecewise function from empirical observations of inputs and outputs, thereby avoiding the need to assume functional relationships between inputs and outputs or to make distributional assumptions regarding the residuals in a regression analysis.

Most of the non-parametric applications are based on the DEA (Data Envelopment Analysis) model as proposed by Charnes et al. (1978). In recent years, DEA has become a central technique in productivity and efficiency analysis, applied in different aspects of economics and management sciences. DEA has been used in comparing organizations (e.g. Athanassopoulos and Shale, 1997; Abbott and Doucouliagos, 2003; Sheldon, 2003), firms (e.g. Färe et al., 1996; Chen and Ali, 2004) and regions or countries (e.g. Karkazis and Thanassoulis, 1998). In agriculture, DEA has also been applied to studies of various products ranging from horticulture and cotton to aquaculture (e.g. Shafiq and Rehman, 2000; Sharma et al., 1999a; Iraizoz et al., 2003. A further comparative review of frontier studies on agricultural products can be found in Thiam et al., 2001). Applications in assessing the efficiency of livestock farms are growing (e.g. Cloutier and Rowley, 1993; Fraser and Cordina, 1999; Reinhard et al., 2000; Fousekis et al., 2001) but they are mostly focused on dairy farms. To our knowledge, previous work on an efficiency assessment of pig farming are limited to Sharma et al. (1999b), who investigated swine production in Hawaii, and to Lansink and Reinhard (2004), who assessed the efficiency of pig farms in the Netherlands.

A key question arising from frontier analysis is whether it is possible to determine common characteristics among best practice units. Existence of such characteristics implies that a certain pattern (behavioural and/or managerial personal characteristics) can be associated with efficiency levels and its influence on farm performance assessed. In the literature, numerous empirical studies attempt to explain variation in the success of farms by regressing efficiency scores on a set of explanatory variables. Most studies concentrate on the influence of personal characteristics such as age, education, experience and specialisation, or physical aspects such as farm size and certain input usage (e.g. Sharma et al., 1999b; Lansink and Reinhard, 2004; Fousekis et al., 2001; Wilson et al., 2001; Iraizoz et al., 2003).

However, Rougoor et al. (1998) suggest that the attempt to explain variation in efficiency based solely on physical or biographical variables may be insufficient; even a farmer with high personal skills may be inefficient, provided his decision-making process (planning, implementation and control of decisions) is poor. Within this context, the purpose of this paper is twofold: first, to specify and measure the efficiency of Greek commercial pig farms and second, to focus on certain managerial aspects of pig farming and investigate the extent to which a set of alternative breeding and production practices may affect a farm's performance.

The remainder of the paper is organised as follows: In the following section DEA methodology is discussed and the applied model is presented. Next, a brief description of the Greek pigmeat sector is given, along with an explanation of the sampling procedure and the definition of the data used in the empirical model. Results are presented and discussed subsequently, while concluding remarks are given in the final section.

2. Methodology and model specification

DEA models are linear programming methods that calculate the frontier production function of a set of decision-making units (DMUs) and evaluate the relative technical efficiency of each unit, thereby allowing a distinction to be made between efficient and inefficient DMUs. Those identified as "best practice units" (i.e., those determining the frontier) are given a rating of one, whereas the degree of technical inefficiency of the rest is calculated on the basis of the Euclidian distance of their input–output ratio from the frontier (Coelli et al., 1998).

According to Farrell (1957), technical efficiency (TE) represents the ability of a DMU to produce maximum output given a set of inputs and technology (output-oriented) or, alternatively, to achieve maximum feasible reductions in input quantities given input prices and output (input-oriented). The choice between input- and output-oriented measures is a matter of concern, and selection may vary according to the unique characteristics of the set of DMUs under study. In this study, input-oriented DEA seems more appropriate, given that it is more reasonable to argue that in the agricultural sector a farmer has more control over inputs rather than output levels, which may often be exogenously bounded (e.g., CAP provisions). In addition, the inelastic demand of most agricultural products renders cost reduction a better means of increasing profitability than output growth, notwithstanding that in many cases the choice of orientation has only minor influences upon the scores obtained (Coelli, 1996).

Assuming constant returns to scale (CRS), TE for a unit that produces k outputs using m different inputs is obtained by solving the following model:

$$\begin{aligned} &\mathrm{Min}_{\theta,\lambda}\theta \\ &\text{subject to} \quad y_i \leqslant Y\lambda, \\ &\qquad\qquad\quad \theta x_i \geqslant X\lambda, \\ &\qquad\qquad\quad \lambda \geqslant 0, \end{aligned} \tag{1}$$

where y_i is the $(k \times 1)$ vector of the value of outputs produced and x_i is the $(m \times 1)$ vector of the value of inputs used for unit i. Y is the $(k \times n)$ vector of outputs and X is the $(m \times n)$ vector of inputs of all n units included in the sample. λ is a $(n \times 1)$ vector of weights and θ is a scalar with boundaries of one and zero that determines the efficiency score of each DMU, i.e., $\theta = 1$ shows a technically efficient DMU; $\theta < 1$ shows a technically inefficient DMU. In order to obtain efficiency scores for each farm, Eq. (1) has to be solved n times, once for each farm.

Banker et al. (1984) developed a variable returns to scale (VRS) frontier by which technical efficiency scores are obtained from a reformulation of Eq. (1) with a convexity constraint $N'\lambda = 1$ (where N is an $n \times 1$ vector of ones) included. By imposing the convexity constraint the data points are enveloped more tightly so that the projected "peers" for a technically inefficient unit are only efficient units of a similar size. Correspondingly, TE scores under VRS ($\mathrm{TE_{VRS}}$) are greater than or equal to TE scores under CRS ($\mathrm{TE_{CRS}}$).

A technically efficient DMU (under VRS, or 'pure technically efficient') may still be over- or under-producing if it is feasible for this farm to alter its size towards the optimal size, i.e., in the region where there are CRS in the relationship between outputs and inputs (Abbott and Doucouliagos, 2003). In such a case, the particular DMU is scale inefficient, which can be determined by running the CRS and the

VRS models on the same data; a difference between the two TE scores indicates a scale-inefficient unit. Hence, scale efficiency (SE) is TE_{CRS}/TE_{VRS}. Although critical, the degree of scale inefficiency is not very useful from a managerial point of view, unless one can determine whether a DMU is operating in a region where decreasing (DRS) or increasing (IRS) returns to scale exist. This information can be obtained if the convexity constraint $N'\lambda = 1$ in (1) is substituted with $N'\lambda \leqslant 1$, thereby allowing both for constant and decreasing (i.e., non-increasing) returns to scale (NIRS). If the two TE scores (TE_{VRS} and TE_{NIRS}) are equal then DRS apply; else IRS prevail.

As mentioned above, the most notable feature of DEA models is that they allow for comparative evaluations of managerial performance. Inefficient units can be projected onto a reference point on the boundary of the production possibility set, that is, onto an input usage set of an efficient unit or a combination of input sets of different efficient units. However, because of its linear piecewise form, a section of the DEA frontier is parallel to the axes. Therefore, and because Eq. (1) measures the distance of an inefficient unit from the frontier only radially (i.e., assuming equiproportional reductions in all inputs) the reference point for an inefficient unit may indeed lie on such a section. In this case, the unit will become technically efficient under the Farrell definition but it will not achieve Pareto-efficiency. The latter requires that no further decrease in any input is feasible without an increase in at least one other input. This case, referred to in the literature as the existence of (input) slacks, is illustrated for the two-input case in Fig. 1. Consider the case with three best practice DMUs (D, E and F) that determine the frontier II′ and three inefficient ones (A, B and C), all using two inputs (x_1 and x_2) to produce the desired output. The vertical and horizontal sections of the boundary DI and EI′ beyond D and E, respectively, are not Pareto-efficient. Hence, only DMUs D and E are efficient under both definitions; unit F is Farrell-efficient but fails to fulfil the stricter Pareto-efficiency definition. The three inefficient DMUs can radially reduce their inputs and move on to the frontier if they adjust to their corresponding projected points A′, B′ and C′, respectively. For unit B, this movement is sufficient for it to become technically efficient under both definitions; for the other two, however, it is not, given that they can further reduce one of their inputs without increasing the other and still maintain the same output level. The projected point A′, for instance, that corresponds to a radial

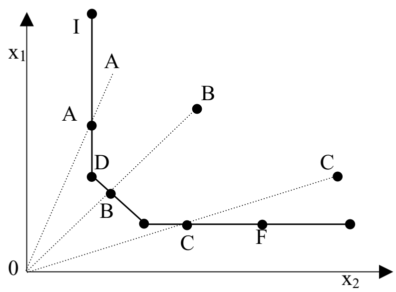

Fig. 1. Radial movements and input slacks in DEA models (2 input case).

(proportional) reduction of inputs x_1 and x_2 for DMU A is not an optimal (Pareto-efficient) point, as a further reduction of input x_1 by A′ D (input slack) is still possible with no reduction in output.

A number of different approaches have been proposed for the handling of slacks and the projection of Pareto-efficient points. Radial measures of TE include the two-stage DEA model (Ali and Seiford, 1993) and the multi-stage DEA (Coelli, 1998), while non-radial measures include the additive model (Charnes et al., 1985) and the Färe and Lovell (1978) model. In this paper the multi-stage DEA model is applied, by which the efficient projected points are determined via a sequential solution of Eq. (1) involving six different steps, each conducting a sequence of radial improvements to input levels until all slacks are eliminated and the reference point is projected onto the efficient subset of technology (i.e., section DE in Fig. 1). This methodology, unlike the additive model, is unit-invariant and identifies the closest reference points (i.e., peers) rather than the furthest ones, as in the two-stage model or the Färe and Lovell model. This is because the two-stage model actually *maximizes* the sum of all input slacks, whereas the Färe and Lovell model identifies the *maximal* average input reductions necessary for an inefficient unit to become efficient.

3. Sample selection and data description

Pork production is one of the most dynamic sectors of the Greek agro-food industry. During the last decade per capita consumption of pigmeat increased steadily, reaching 23 kg in 1997, around 30% of total meat consumption. Production has been growing but is primarily directed towards the domestic market, as self-sufficiency levels are lower than 60% (Apostolopoulos et al., 2001). Nevertheless, the annual rate of growth of exports in the period 1990–1998 was around 30%, while the significantly larger imports increased by 15% to around 185,000 t.

The pork production system in Greece has undergone considerable changes over the last few decades, evolving from a family-type operation with a herd size of 10–20 sows to an industrialised, indoor-type operation with a significantly larger average herd size. The main actors involved in the supply chain of pork are the producers, the processors, the wholesalers and the retailers (butcheries and large retail outlets). Pork is marketed down the supply chain via one of the following routes: (a) the producer sells live animals to the processing units, (b) the producer sells carcasses to wholesalers or retailers and (c) the producer sells carcasses in own butcher shops. Today, there are 97 processing units, including both small, traditional ones, operating mainly as slaughterhouses for all kinds of livestock, as well as large processing firms involved in the slaughtering, standardisation and packaging of pork. The latter are gradually gaining market share as they are benefiting from contractual agreements with large retail outlets.

For this empirical analysis, a field study was conducted on 100 pig farms located in the most important pig farming areas in Greece. These prefectures (as shown in Table 1) represent around 40% of the total number of commercial pig farms (farms with minimum 20 sows) in Greece and 57% of the total number of sows.

Table 1
Geographic distribution and classification of pig farms in Greece

Prefectures	20–199 sows		200–399		>400		Total	
	Actual	Sample	Actual	Sample	Actual	Sample	Actual	Sample
Sterea Ellada	49	15	36	15	68	9	153	39
Attici-Voiotia	24	6	18	4	12	3	54	13
Evia	12	4	10	4	36	3	58	11
Aetoloakarnania	13	5	8	7	20	3	41	15
Thessaly	110	31	24	13	48	7	182	51
Trikala	78	18	8	4	24	3	110	25
Larissa	22	9	11	6	17	2	50	17
Karditsa	10	4	5	3	7	2	22	9
Macedonia	12	5	5	3	6	2	23	10
Drama-Xanthi	12	5	5	3	6	2	23	10
Total	171	51	65	31	122	18	358	100

Questionnaires were administered to get insights into the performance of pig farms, conducted through longitudinal personal visits in 1997/1998. Data on management practices were gathered in all areas of the production process, i.e., pasture, feeding, animal health, fertility and breeding, as well as technical and economic data. In order to ensure the integrity of the sampling selection process, a multistage cluster method was applied. Based on this method, farms located in the areas under study ($n = 358$) were classified into three groups according to their number of sows: S_1: 20–199, S_2: 200–399 and S_3: more than 400 (Table 1). The sample originally included 100 pig farms, representing 28% of the number of farms in the study areas and around 11% of the total number of pig farms in Greece ($n = 920$). During the processing of the collected data, 20 farms were dropped, because of incomplete or unreliable responses. Ultimately, 80 farms comprised the sample, geographically distributed as follows: 44 in Thessaly, 5 in Macedonia, 17 in Attici, Voiotia and Evia and 14 in Aetoloakarnania.

The DEA model applied in the current study consists of one output (gross returns of pig farm) and four inputs. Gross returns include revenues from pork production only, i.e., all other potential sources of revenues have been excluded. Inputs include labour, capital, feeding expenses and all other expenses. Labour includes family and hired labour and is measured in hours per year. Capital includes interest costs (short- and long-term debt), depreciation, maintenance, insurance and other annual expenses of fixed assets (i.e., buildings and machinery). Feeding expenses represent the annual cost for feedingstuff, while other expenses are the summation of all other variable costs (veterinary services, transportation, electricity, taxes etc.). All parameters have been normalized by an additional variable, namely, the number of sows, in order to increase the variation of the selected variables and to investigate whether pig farms in Greece have an optimal size relative to the number of sows.

The use of linearly aggregated inputs in the DEA model (i.e., use of aggregated expenditure categories rather than actual input levels) has several drawbacks.

Table 2
Descriptive statistics of the variables used in the DEA model

Variable	Unit	Mean	St. dev	Min	Max
Gross returns	€/sow	1814.98	362.26	646.08	2644.83
Labour	Hours/sow	44.01	21.42	16.46	171.60
Capital	€/sow	2.83	1.53	0.90	9.57
Feed	€/sow	1073.57	285.69	366.31	1608.88
Other expenses	€/sow	692.89	199.06	208.21	1043.39
No. of sows		268.13	232.50	30.00	1300.00

Thomas and Tauer (1994) show that the use of value-aggregated inputs may result in failure to distinguish between technical and allocative effects and also that the ranking of the DMUs can change with different aggregation levels. Ultimately, such aggregation imposes a production structure on the production processes being aggregated, which is a source of potential bias in estimating technical efficiency.

On the other hand, the use of aggregated expenditure categories could be the only solution in cases where the use of actual input levels would result in either too many inputs included in the model or to the exclusion of certain inputs. In both cases, results can also be biased, given that, in the former case the inclusion of additional input variables in the DEA model results in increased efficiency scores, whereas in the latter case, the omitted variables could be of significant magnitude. Hence, value-aggregation is often applied in the relevant literature (see for instance Sharma et al., 1999a,b; Iraizoz et al., 2003; Lansink and Reinhard, 2004). The multi-stage DEA method that is applied in this paper is invariant to units of measurement (Coelli, 1998), thereby ensuring that the ranking of the DMUs will be consistent regardless of aggregation levels.

Table 2 presents the descriptive statistics of the variables used in the analysis. A wide variation in both the input use and the output is noticeable. The output obtained is in some cases four times larger than that achieved by other farmers, while variation in input variables is even higher; some farmers have 10 times higher labour and capital costs than others, whereas variation in feed costs and other expenses is around four and five times, respectively. Such a variation in the input levels certainly suggests that certain levels represent poor resource management by farm owners. In addition, this may not be completely unexpected, given that the sample was drawn as representative of the Greek production system whose characteristic is the co-existence of small family-type farms with large, industrial farms. Consequently, included in the sample are farms with as much as 43 times more sows than others, a fact that could justify the variation in input use levels.

4. Results and discussion

4.1. Technical and scale efficiency

Results obtained by the application of the input-orientated DEA are illustrated in Fig. 2. Seven farms (8.8%) are best practice under CRS and 15 (18.8%) under VRS.

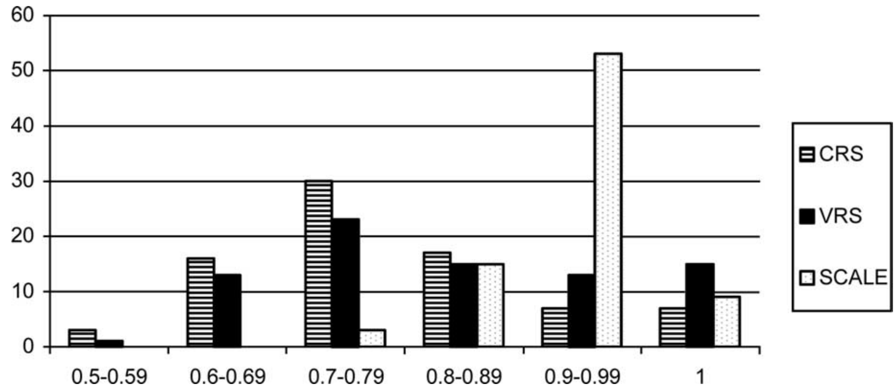

Fig. 2. Distribution of technical and scale efficiencies.

Although the number of technically efficient firms is not small, the mean radial technical efficiency of the sample is 0.782 and 0.828 under CRS and VRS assumptions, respectively. This implies first, that on average, farms could reduce their inputs by 21.8% (17.2%) and still maintain the same output level, and second, that there is considerable variation in the performance of pig farms in Greece. There are some farms that operate either on or close to the frontier, but still, 62% of the farms exhibit technical inefficiencies greater than 20%. For comparison reasons, we note that our findings lie in-between Sharma et al. (1999b) who report 0.64 and 0.76 average technical efficiency under CRS and VRS, respectively, in their study of Hawaiian swine production and Lansink and Reinhard (2004), whose corresponding figures are 0.89 and 0.9 for the Netherlands.

The interpretation of the scale efficiency scores allows for some interesting remarks. Mean scale efficiency is 0.947, implying that the average size of Greek pig farms is not far from the optimal size, although an additional 5.3% productivity gain would be feasible – assuming no other constraining factors – provided they adjusted their farm operation to an optimal scale. By contrast, Lansink and Reinhard (2004) report a higher (0.98) scale efficiency for pig farms in the Netherlands. Only nine farms (11%) are actually operating at the most productive scale where CRS apply and scale efficiency equals one. The majority of the scale-inefficient pig farms (46, or 65%) are operating under decreasing returns to scale (i.e., at a point corresponding to the upward portion of the Long-Run Average Cost curve) and the remaining 25 under increasing returns to scale. Efficiency analysis theory suggests that the latter are obviously small farms that need to increase their size in order to achieve cost savings, whereas the former are larger farms that have expanded more than necessary and thus would be better off by reducing their size. This finding is inconsistent with the overall picture of the Greek agricultural sector characterized by small farm size; Fousekis et al. (2001), for instance, report opposite results when comparing sheep farms in Greece. Three points could explain this contradiction. First, Fousekis et al. (2001) examine a different livestock sector whose structural characteristics are different from those of pig farming. Second, in this paper we have focused on the commercial segment of pig farming and therefore our sample consists of pig farms with more than 20 sows, thereby excluding the very small, family-type farms. Third and most importantly, given that all variables have been normalized by the number of sows, scale inefficiency measures actually indicate that the size of a farm might be too large relative to the number of sows. In this sense, scale efficiency gives a better insight of the structure of pig farms in Greece. Even small farms might be operating on a larger, non-optimal scale; when the DEA model was applied on the same un-normalised data, mean efficiency scores did not alter significantly, but returns to scale did: 66% of the sample exhibited IRS.

The classification of pig farms according to their size class shows that on average the larger farms (more than 400 sows) are more technically efficient than medium- and small-sized farms (Table 3). Large farms are also more scale-efficient, as their average size is only 2.8% away from the optimal size. Consequently, it can be argued that size is a crucial element in the economic viability of pig farms. Smaller farms are impeded by greater technical inefficiencies whereas the large farms achieve better performance benefiting both from increased technical efficiencies as well as from greater economies of scale.

Table 3 also presents the distribution of efficiency scores across the four study regions. Farms located in East Sterea (prefectures of Attici, Voiotia and Evia) are the most technically efficient units, and are considerably more efficient than the farms located in West Sterea. On the other hand, only Macedonia shows significant scale inefficiencies whereas the other regions exhibit similar scores. In an attempt to explain these results, one may note the association of farm size and efficiency scores. In East Sterea where the local farms exhibit the highest mean TE score, the average number of sows is 370.6, considerably higher than the corresponding numbers in the other three regions (202, 230 and 275). Not surprisingly, farms in Macedonia, characterised by the smallest number of sows per farm, although not the most technical inefficient, are the ones who benefit the least from economies of scale.

Table 3
Average efficiency scores according to size and location

	TE_{CRS}	TE_{VRS}	SE
Overall sample mean	0.782	0.828	0.947
Classification by size			
Less than 200 sows	0.765	0.820	0.934
200–399	0.769	0.811	0.953
More than 400	0.841	0.866	0.972
Classification by area			
Macedonia	0.768	0.847	0.902
Thessalia	0.786	0.825	0.953
East Sterea	0.804	0.858	0.940
West Sterea (Aetolakarn.)	0.749	0.789	0.955

TE: Technical Efficiency; CRS: Constant Returns to Scale; VRS: Variable Returns to Scale; SE: Scale Efficiency.

Perhaps the most notable feature of DEA is that it can provide useful information and evidence for a managerial evaluation of all DMUs separately, thereby identifying and assessing the exact sources of inefficiencies for each unit. This process enables a DMU to highlight where the greatest gains can be made from improvements in efficiency and help them achieve their full potential (Abbott and Doucouliagos, 2003). As an illustration, we choose the case of the most technical inefficient pig farm in the sample, which is DMU 1. For this analysis we look at the results obtained by the VRS DEA model (i.e., pure technical efficiency). It may be recalled that the assumption of constant returns to scale is appropriate only when all DMUs are operating at an optimal scale. The results presented above do not support this argument, as only a small fraction of the pig farms in the sample is optimally sized. Furthermore, a priori expectations regarding the pig-farming sector in Greece further justify this argument. The existing wide variation in the size of farms ranging from family-type to well organized industries indicates the presence of an imperfectly competitive market structure, in the sense that the latter have easier access to finance and credit services, they can benefit from higher bargaining power regarding bulk input orders or produce sales, etc.

TE_{VRS} for DMU 1 is 0.587, implying that the farm could become technically efficient (under the Farrell definition) provided it reduced all its inputs proportionally by 41.3%. Hence, the analysis suggests that input use could be reduced to those shown in the third row of Table 4 while maintaining current production levels, assuming no other constraining factors. However, this farm would not be Pareto-efficient, as it would be operating on the vertical section of the production frontier. In order to project a Pareto-efficient point, a further slack adjustment is necessary. Ultimately, DMU 1 has to reduce all inputs by 41.3% and labour, capital and feeding expenses by another 26%, 3.7% and 5.4%, respectively, in order to be operating at a fully technically efficient point (last row of Table 4).

This point is equivalent to adjusting to the production practices of its corresponding peers. For a sample of DMUs, DEA not only separates the efficient units from the inefficient ones, but also computes the efficient input levels for inefficient units in terms of linear combinations of input and output levels of efficient units. Taking another inefficient DMU – DMU 56 – as an illustration, with a technical efficiency score of 0.64, its identified peers are DMUs 5, 8, 70 and 73. Table 5 compares the actual input mix of DMU 56 against those of its peers. It can be seen that the

Table 4
Actual and efficient input use levels of DMU 1

	Inputs			
	Labour (hours/sow)	Capital (€/sow)	Feeding (€/sow)	Other exp. (€/sow)
Actual values	171.60	4.65	1472.96	732.88
Radial movement	−70.87	−1.92	−608.33	−302.68
Projected point	100.73	2.73	864.62	430.20
Slack adjustment	−44.64	−0.17	−79.18	0.00
Pareto-efficient point	56.09	2.56	785.44	430.20

Table 5
Input use levels of DMU 56 and of its peers

	DMU 56	Input use levels of peers				Input targets
		DMU 5	DMU 8	DMU 70	DMU 73	
Lambda		*0.03*	*0.09*	*0.78*	*0.11*	
Inputs						
Labour (hours/sow)	37.37	72.00	25.20	18.87	48.00	23.93
Capital (€/sow)	1.94	2.64	1.76	0.90	2.93	1.24
Feed (€/sow)	1066.23	479.03	366.31	754.00	481.47	682.82
Other expenses (€/sow)	811.28	303.67	208.22	517.21	377.46	468.83
Output						
Gross Returns (€/sow)	1580.38	1467.36	646.08	1700.23	1526.42	1580.38

inefficiency of DMU 56 is attributed to the excessive use of inputs, especially regarding labour and feeding expenses. Because DMU 56 has more than one peer, it is essential to identify how much each peer influences the projected efficient production point. Based on the lambda values obtained by solving Eq. (1), it is clear that DMU 70 is the most influential benchmark, representing 77.7% of the ideal peer for DMU 56. The lambda values are weights to be used as multipliers for the input levels of a reference farm to indicate the input targets that an inefficient farm should aim at in order to achieve efficiency. These input targets for the inefficient DMU are shown in the last column of Table 5.

The preceding analysis provides useful information to a farm manager in determining excessive use of inputs and assessing alternative production strategies. The identification of the farms that should be used in terms of benchmarking allows the establishing of the most appropriate best-practice management relative to the particular characteristics of each individual farm.

However, the DEA analysis can neither fully explain the underlying differences in efficiencies in the use of a particular input, nor assess the constraints to changes in operational practices that would improve efficiency. Therefore, given the limits on the usefulness of the information obtained, efficiency analysis should only be considered a starting point for identifying places to make improvements in farm production systems rather than an ending point.

4.2. Assessment of breeding and production practices that can affect farm efficiency

It is common, after obtaining efficiency scores for the sample DMUs, to attempt to explain variations in efficiency scores by regressing efficiency scores on certain explanatory variables. This study concentrates particularly on managerial and breeding practices and investigates the extent to which they might influence the efficiency of a pig farm.

The exogenous variables on which efficiency scores have been regressed are the number of sows (NSOW), the mortality rate of new-born and suckling piglets (MORT) and six dummies capturing a set of breeding and nutrition practices that are of crucial importance for a pig farm and are therefore expected to affect its efficiency. The choice of insemination method, for instance, is recognized as an important element of pig farming management, and artificial insemination is considered technically superior to natural service (Whittemore, 1993). INSEM takes the value of one for farms that make use of artificial insemination and zero otherwise.

The origin of the genotype has also a significant impact on the herd's characteristics. Breeding scientists favour a genotype provided from breeding stocks rather than from finishers, as the former method ensures an increased rate of quality characteristics transfer from one generation to another (i.e., shorter fattening period, higher disease tolerance). GENTYPE takes the value of one in the case of a farm utilizing the first method and zero otherwise.

Feeding is perhaps the most crucial element of pig farming. Apart from constituting the largest part of total costs, the choice of feeding ratio (i.e., composition and quality of ingredients and supplements, percentage of vitamins and micronutrients, etc.) has a significant impact on the herd's health and quality. FEED is one if self-prepared (on-farm) and zero if bought already made. A priori expectations suggest that as the farmer has no control over the bought feed mixes, quality and adaptation to the herd's particular needs are not ensured and should therefore be associated with lower efficiency levels.

Weaning is a dummy that takes the value of one if the farmer applies early weaning (less than 15 days) and zero otherwise. Finally, a personal characteristic variable was also included, namely the farmer's education level (EDU; 0 = elementary school; 1 = hi-school degree or higher education). Ultimately, two models have been constructed, one assessing the influence of these variables on pure technical efficiency and the other on scale efficiency.

In cases such as this, where the dependent variable (i.e., inefficiency scores) is equal or greater than zero, a Tobit regression with lower limits is more appropriate (Tauer and Stefanides, 1998; Sharma et al., 1999b). The applied Tobit model is defined as:

$$y_i^* = x_i\beta + u_i \quad \text{With the observed data } y \text{ given by:} \quad y_i = \begin{cases} 0 & \text{if } y_i^* \leqslant 0, \\ y_i^* & \text{if } y_i^* > 0, \end{cases} \tag{2}$$

where y_i^* is the latent variable, x_i denotes the vector of explanatory variables, β denotes the relationship between the latent and the explanatory variables and u_i is random error, normally distributed with mean zero and variance σ^2.

Prior to the interpretation of the results, it should be stressed that as in other limited dependent variable models, the estimated coefficients in Tobit regression models do not have a direct interpretation as a true marginal effect but rather a two-scale effect: an effect on the mean of the dependent variable, given that it is observed, and an effect on the probability of the dependent variable being observed. Therefore, the marginal effects calculated at the mean of the data rather than the coefficients themselves are reported here, so as to make interpretation of the coefficients clearer.

Table 6
Results of Tobit regression on technical and scale efficiency

	TE_{VRS}		SE	
	Coefficient	St. error	Coefficient	St. error
Intercept	0.0606		0.0054	
NSOW	−0.0001[c]	0.0001	−0.0001[c]	< 0.0001
MORT	0.0133[c]	0.0072	−0.0004	0.0053
INSEM	−0.0571[b]	0.0250	−0.0097	0.0171
GENTYPE	−0.0812[a]	0.0198	0.0183[b]	0.0089
WEAN	0.0381	0.0465	−0.0060	0.0211
FEED	0.1730[a]	0.0540	0.0317[b]	0.0149
EDU	0.0316	0.0331	0.0197	0.0148
White's test[d]	10.8350	(0.3705)	10.4112	(0.4052)

Coefficients represent marginal effects calculated at the mean of the data.
TE_{VRS}: Technical Efficiency under variable returns to scale; SE: Scale Efficiency.
[a] Significant at the 1% level.
[b] Significant at the 5% level.
[c] Significant at the 10% level.
[d] White's test of heteroscedasticity. Test statistic follows a χ^2 distribution with degrees of freedom equal to the number of variables (excluding the constant) included in the auxiliary regression. Values in parentheses are P values.

For the results presented in Table 6, the independent variable is the inefficiency score, so a positive (negative) sign of a coefficient reflects a negative (positive) effect on efficiency levels.

With that in mind, the farm size, as reflected by the number of sows, has a positive impact on efficiency levels, suggesting that larger farms are more efficient than smaller ones. The mortality level has, as expected, a positive sign, indicating that higher mortality levels can be associated with decreased efficiency levels. Additionally, the choice of artificial insemination as the reproduction method and the use of breeding stocks as the genotype source appear to increase the ability of a farm to operate at best-practice levels, as indicated by the negative signs on their corresponding coefficients.

Early weaning practice has a positive correlation with inefficiency but is not statistically significant. This may not come as a surprise: early weaning contracts the breeding period and thereby reduces production costs but on the other hand it may be associated with higher disease and mortality rates. The farmer's education level dummy has an unexpected sign indicating a negative correlation between education and efficiency, but is also not significant.

Perhaps, the most surprising result is the sign of FEED. Contrary to a priori expectations, it is positive, thereby indicating that the on-farm feed preparation system does not enhance the efficiency of a pig farm. This system is usually preferred from a technical point of view, as it allows for better control of quality and supplement intakes, and is generally more flexible in terms of the particular needs of each herd. On the other hand, purchased feeds may be better formulated or accompanied by the services of a nutritionist who can help formulate feeds that better meet the nutritional needs of the animal. This latter effect could be reflected in, and at least partially explained by, the positive sign for the FEED variable.

5. Conclusions

An input-oriented DEA model has been applied in order to investigate the degree of technical and scale efficiency of commercial pig farming in Greece. This procedure allows the determination of the best practice farms and can also provide helpful insights for farm management. By using these farms as benchmarks, inefficient farms can determine which changes in resource use are necessary in order to increase their overall performance and, ultimately, their profitability.

This paper shows that the transformation of all inputs (capital, labour, feeding, other expenses) and outputs (gross returns) to average per sow expenses, may provide a clearer insight into farm performance as efficiency scores can be more realistic and closer to the actual performance of each farm. In addition, it reveals that even smaller farms may have expanded to a size larger than that required by their number of sows and are consequently operating under decreasing returns to scale. Results suggest that on average, a potential 17% reduction in input use could be achieved provided all pig farms operated efficiently, assuming no other constraints on this adjustment. In general, larger farms appear to be more technically efficient than smaller farms.

These results are of importance for the pig farming sector. Following the general tendency of worldwide agricultural trade liberalization due to the ongoing WTO negotiations and the recent EU enlargement process, the level of competition is expected to increase. The pig farming sector will unavoidably be affected as well, leading to a more market-orientated sector characterised by increased competition and imports, reduced statutory subsidies, export supplements and intervention measures. Within this context, farmers need to adapt to these changes if they are going to remain profitable. The reduction of input wastes and costs may prove the most effective means of enhancing the viability of pig farms, given that farmers have more control over inputs. Moreover, as competition increases and Community prices are stagnant or even falling (European Commission, 2004), the need to achieve efficient levels of input usage becomes crucial for all farmers. The methodology presented in this paper demonstrates how farmers may benefit from applying operational management tools to assess their performance. Increasing the technical efficiency of a farm actually means less input usage, lower production costs and, ultimately, higher profits, which is the driving force for farmers' motivation to adopt new techniques.

Given that inefficiency variation among the sample farms was large, we investigated whether efficient pig farms share certain common characteristics in terms of management practices. Results indicate that a number of managerial and breeding practices may affect a farm's performance. The use of both artificial insemination and genotypes provided from breeding stock is positively correlated with efficiency, suggesting that these two factors can be associated with increased farm performance.

On the other hand, on-farm preparation of feed mixes has a negative and statistical significant effect on the efficiency of pig farms. This result warrants further investigation, as this practice is usually associated with advanced management operation. Early weaning and the education of the farmer do not appear to have a significant impact on efficiency levels.

Undoubtedly, additional research is required to generalise the evidence provided in this study, in particular regarding the explanation of the underlying differences in efficiencies in the use of a particular input and the assessment of the constraints to changes in operational practices that would improve efficiency. Nevertheless, some interesting insights regarding the performance of the pig farming sector in Greece, along with an indication of the relationship between certain managerial and breeding practices and technical efficiency, may have been provided.

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