Efficiency analysis in a sample of PGI bean producers in Greece

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Abstract

This paper provides an evaluation of the performance of a sample of PGI bean producers in Greece, by means of technical and scale efficiency and a comparison between them on the basis of average efficiency, aggregate efficiency and the performance of the average production unit. Data were collected from 104 farms in 2012-2013, using a structured questionnaire, with face-to-face interviews, within the designated area of protected geographical indication. Results revealed that technical rather than scale inefficiency is the main source of productive inefficiency, with corresponding efficiency estimates of 0.837 and 0.949 respectively. Most farms (87%) operate in a sub-optimal scale and are less technically and scale efficient than farms working in a supra-optimal scale (6%).They are 14 technically efficient farms in the sample (13%) of which almost half are both technically and scale efficient. The systematic comparison of the performance of PGI bean farms provided four dominating farms appearing more often as peer-units, information that is valuable for performance improvement targets.

Keywords: *Scale and technical efficiency, Structural and average efficiency, DEA, PGI beans*

1. Introduction

The voluntary participation by EU farmers in quality assurance schemes for agricultural products of geographical origin is growing, as it offers substantial benefits through product and market differentiation and the creation of market niches. In addition, the intrinsic link between a quality label and a geographical location creates positive externalities for the whole region through the added value gained by producers and a collective reputation that benefits other local products, as well as tourism. A large number of the European foodstuffs bearing such labels are produced in less advantaged often mountainous regions and the external benefits associated with quality labels are greatly valued for their effect on rural development (IP/B/AGRI/IC/2012-067 PE 495.856 EN; BUREAU and VALCESCHINI, 2003).

Greece has 101 quality labeled products, PDO (protected designation of origin) and PGI (protected geographical indication) of plant or animal production, which brings it in the fifth place in terms of the number of certified goods in the EU, yet accounts for a market share only a little above 1% within the European market(Reg. (EU) No 1151/2012; ec.europa.eu/agriculture/quality/door). Three of the 27 Greek PGI commodities are dry beans produced in the northwestern part of the country. In particular, two of them are produced around the Prespes lake area in the province of Florina, a geographical area with unique geomorphological and climate conditions, and the third one is produced in the next by province of Kastoria. Their shares in the regional bean production are around 60% and 40%, respectively (ELSTAT, 2011; FAO, 2013). Approximately 230 farms produce the two types of dry beans within the designated geographical zone in the province of Frorina and 212 in the province of Kastoria.

Bean cultivation has been declining over the last three decades in Greece from 33.900 ha in 1980, to less than a third (9.062 ha in 2013), with production dropping from 42.040 tons by about 40% (25.000 tons). In the 1980's Greece was self-sufficient in that product exporting minor quantities, yet, today there is a trade deficit with local production covering about 60% of the country' s needs and main sources of imports are the USA, Canada, Albania and Argentina. Against these, the introduction of the EU policy on quality schemes for agricultural products and foodstuffs, turned out to be very favorable for three bean producing areas that opted for the certification of their local bean varieties and gained a comparative advantage. However, in recent years there has been limited growth in both the area under cultivation and bean production in the region, despite the advantages provided by the PGI label.

The aims of this paper is to examine the extent and the sources of inefficiency in the production of PGI dry beans in the province of Florina using a representative sample of almost half of the population of PGI dry beans farmers in the province. For these purposes we employ Data Envelopment Analysis (DEA) and we estimate efficiency scores at both the individual and the aggregate level. For the former we estimate productive, technical and scale efficiency and for the latter we impute, using the individual scores, aggregate and structural efficiency. We further explore the characteristics of the best practice peer group by means of metrics such as their reference and benchmarking shares. These would provide policy makers with helpful insights about the profile of successful operators that may help local producers to improve their performance and in turn their farm income.

In the efficiency literature, a fairly limited number of papers refer to quality labeled production. DIMARA et al. (2005) considered the production of black currant in Greece and estimated farm efficiency in two distinct quality schemes, namely conventional production under a PDO label and organic farming inside or outside the PDO zone, with only the former farming practice's efficiency being affected by the PDO status. IRAIZOZ et al. (2011) carried out a comparative analysis of PGI and non PGI-certified beef farms in Spain in terms of economic performance, profitability and efficiency, where PGI farms achieved higher levels of profitability and scale efficiency but lower-though not significant- productive efficiency. VIDAL et al. (2013)) analyzed The efficiency and productivity analysis of a panel of Spanish DO (Designation of Origin) wine producing firms and shown that their productivity performance was more or less unchanged, with the larger farms being the most inefficient. APARICIO et al. (2013), considering thesame sample of DO wine producers,concluded that technical rather than allocative efficiency was the main source of underperformance.

The rest of this paper is organized as follows: in the next section we present the methodology used to estimate individual and aggregate efficiency and the metrics used to identify influential peers. The data used in the empirical analysis are described in the third section. The empirical results are analyzed in the forth section and concluding remarks following in the last section

2. Methods and Materials

In this section we present the methods to be used for evaluating the performance of the sample of bean producers. First we assess the relative achievements of the sample PGI dry beans farms by means of technical and scale efficiency and then we compare them against some standard metrics used in the literature, namely average efficiency, aggregate efficiency, and the performance of the average production unit.

For these purposes we employ DEA to estimate the benchmark and the best practice frontiers. As in most agricultural studies, we use an output-oriented approach since farmers have control over the different inputs they use but not over the output they produce due to weather uncertainty regarding rainfall and temperature. The estimated output-oriented efficiency scores indicate how much they could have increase their output using the same level of inputs and the same technology if they had eliminated the different sources of inefficiency.

The benchmark frontier corresponds to the maximum average productivity function for the given input-output combinations of the sample units and it would be estimating by means of the underlying constant-returns-to-scale technology, which in turn consists our reference for measuring productive efficiency. In terms of the envelopment form of the CHARNES, COOPER and RHODES (1978) model, the radial output-oriented measure of productive efficiency is given by the solving for each farm in the sample the following linear programing problem:

$$F_0^k(x^k,y^k) = \max_{\varphi,\lambda}\left\{\varphi : \sum_{k=1}^{K} \lambda_n^k x_n \le x_n^k \ \forall\, n,\ \sum_{k=1}^{K} \lambda_n^k y^k \ge \varphi y^k,\ \lambda_n^k \ge 0 \ \forall\, k\right\} \qquad (1)$$

where$x$ and y refers respectively to input and output quantities, λ_n^k are the intensity variables, x_n are ($1xK$) row vectors of the sample input matrix X with elements the quantities of a particular input that are used by the K firms in the sample, y is a scalar, $n=1,\dots,N$ is the number of inputs, and $F_0^k(x^k,y^k) \ge 1$. The restrictions on the intensity variables are related to the structure of returns to scale and the above formulation implicitly assumes constant returns to scale for the whole range of output quantities. In the single output case, as the one considered here, the radial output-oriented measure of productive efficiency is reduced to the ratio of benchmark to observed output, and thus measures the (inverse of the) extent by which the observed output falls short of the benchmark output associated with the observed inputs use. In geometric terms, it corresponds to the vertical distance of an observed input-output combination from the benchmark frontier.

The best practice frontier, on the other hand, corresponds to the tightest envelopment of the observed input-output combinations and would be estimated by means of the underlying variable-returns-to-scale technology, which in turn consist our reference for measuring technical efficiency. In terms of the envelopment form of the BANKER, CHARNES and COOPER (1984) model, the radial output-oriented measure of technical efficiency is given by the solving for each farm in the sample the following linear programing problem:

$$E_0^k(x^k,y^k) = \max_{\theta,\mu}\left\{\theta : \sum_{k=1}^{K} \mu_n^k x_n \le x_n^k \ \forall \ n, \ \sum_{k=1}^{K} \mu_n^k y^k \ge \varphi y^k, \ \sum_{k=1}^{K} \mu_n^k = 1, \mu_n^k \ge 0 \ \forall \ k\right\} \tag{2}$$

where $E_0^k(x^k,y^k) \ge 1$. In the single output case, the radial output-oriented measure of technical efficiency reduces to the ratio of best practice to observed output, and thus measures the (inverse of the) extent by which the observed output falls short of the best practice output associated with the observed input bundle. In other words, it gives the percentage increases in output that is possible with the present amount of inputs if the existing technology had been used more efficiently. In geometric terms, it corresponds to the vertical distance of an observed input-output combination from the best practice frontier. As the convexity constraint related to variable returns to scale (i.e., the sum of the intensity variable being equal to one) is more restricted than the non-negatively of each intensity variable required in the constant returns to scale technology, we have $E_0^k(x^k,y^k) < F_0^k(x^k,y^k)$.

Related to both benchmark and best practice technology is the notion of scale efficiency (FORSUND and HJALMARSSON, 1979). In particular, the output-oriented measure of scale efficiency is given as:

$$S_0^k(x^k,y^k) = \frac{F_0^k(x^k,y^k)}{E_0^k(x^k,y^k)} \tag{3}$$

where $S_0^k(x^k,y^k) \ge 1$. It measures the distance to optimal scale after moving a farm to the best practice frontier in the vertical direction. That is, scale efficiency gives the potential output that a farm could produce operating at the optimal scale and assuming that its technical inefficiency (if any) has been removed (FORSUND, 1996). In geometric terms, scale efficiency is equal to the ray average productivity after the observed output is projected to the best practice frontier relatively to what could be produced at the technical optimal scale. The technically optimal scale is determined by the point(s) in the input-output space that correspond to local constant returns to scale and yield the maximum ray average productivity. Combining the estimation results regarding the nature of returns to scale and scale inefficiency we can examine whether individual farms should expand or contract to reach the optimal scale. In particular, suboptimal (supra-optimal) scale associated with increasing (decreasing) returns to scale requires output to expand (contract) to reach the most productive scale size.

By elaborating relation (3) we can see that benchmarking performance, i.e., the extent of efficiency with respect to the constant-returns-to-scale technology, may be decomposed into a best practice performance component, i.e., the extent of technical efficiency with respect to variable returns to scale frontier, and a scale component related to the extent of deviation from the optimal scale size.

$$F_0^k(x^k,y^k) = E_0^k(x^k,y^k)\, S_0^k(x^k,y^k) \tag{4}$$

This decomposition provides useful information regarding the sources of productive inefficiency and determines the portion of inefficiency that is due to producing below the best practice frontier and that to operating at an inefficient scale size. Moreover, it may help designing more appropriate policy measures to reduce or even eliminate resource waste.

More insights on designing policy measures to improve individual performance may be offered by examining the profile of peer unit(s). These are the efficient units that make up (by means of linear combinations) the reference set of inefficient units. Two rather simple metrics for this purpose are how many times an efficient unit appears as a peer and the magnitude of the intensity variables that corresponds to it. DMUs that appear more times as a peer for inefficient units seem to have more suitable activity profiles than self-evaluators, which although efficient operate with dissimilar to inefficient DMUs activity profiles. On the other hand, using the per inefficient unit best practice intensity variables we can find the most influential peer(s), which are identified with the largest intensity variable (KITTELSEN and FORSUND, 1992). As $\sum \mu_n^k = 1$, each best practice intensity variable express something like percentage importance.

Two other more sophisticated metrics used to identify the importance of peer(s) are the reference and the benchmarking shares. According to TORGENSON et al. (1996), the reference share of an efficient DMU gives the fraction of total aggregate potential output for increases in output for which this particular efficient unit acts as a referent. In particular,

$$\rho^k = \frac{\sum_{n=1}^{K} \mu_k^n (\tilde{y}^n - y^n)}{\sum_{n=1}^{K} \tilde{y}^n - \sum_{n=1}^{K} y^n} \tag{5}$$

where a tilde over y indicates potential or best practice output for the n[th] unit. The larger the value of ρ^k is the larger the importance of the k[th] efficient unit in shaping total aggregate potential output. On the other hand, Johnson and Zhu (2003) defined the benchmarking share of the k[th] efficient unit as:

$$\delta^k = \frac{\sum_{n=1}^{K} \mu_n^k}{\#\ of\ inefficient\ DMUs} \tag{6}$$

That is, for each efficient unit, sum the values of the intensity variables corresponding to this unit over all inefficient DMUs for which appears as a peer and divide it by the number of inefficient units. Larger values of δ^k indicate that there is a higher concentration of performance levels around this particular peer's figures. Notice that both ρ^k and δ^k are zero for efficient units that do not appear as peers for any unit except for themselves, i.e. the self-evaluators.

After examining the technical and scale efficiency scores at the individual level we proceed by comparing then with several summary efficiency measures, such as average efficiency, aggregate efficiency and the performance of the average production unit (APU). Average efficiency is the metric that most of the time is used to infer how well the group of the sample units performs. Nevertheless, it has been shown (KARAGIANNIS, 2015) that average efficiency reflects accurately the performance at the group level only when size and efficiency are uncorrelated. Otherwise, it is not an appropriate performance measure at the group level. To see this notice that average efficiency is an aggregate efficiency measure that assigns equal importance to all units regardless of their size. However, the theoretically consistent measure of aggregate output-oriented technical efficiency is the weighted average of individual efficiency scores with the weights being their output share (FARE and ZELENYUK, 2003; FARE and KARAGIANNIS, 2014); that is,

$$E_0\left(x^1,\dots,x^K, \sum y^k\right) = \sum_{k=1}^{K} s_0^k E_0^k(x^k,y^k) = \sum_{k=1}^{K} \left(\frac{y^k}{\sum y^k}\right) E_0^k(x^k,y^k) \qquad (7)$$

One can verify (see KARAGIANNIS, 2015) that average efficiency is lower (higher) than aggregate efficiency when larger units are more (less) efficient than smaller ones.

On the other hand, the efficiency of the APU--defined as a unit operating with the group (arithmetic) mean quantities of inputs and outputs --is estimated by included it in the sample as another DMU (see FORSUND and HJALMARSSON, 1979). This means that the constraints in the linear programming problems for the benchmark and the best practice frontiers are extended to k=1,…,K+1, where the K+1th unit is the APU, and we run them one more time to estimate the productive and technical efficiency of the APU. It has been shown (LI and CHENG, 2007) that the efficiency of the APU reflects accurately performance at the group level as long as resource reallocation across the farms in the group is allowed. In that sense it reflects structural efficiency. Structural efficiency differs from aggregate efficiency by the extent of reallocation allocation efficiency, which measures by how much group performance may increase by reallocating inputs among the sample farms, even if they are technically efficient.

3. Data and Definition of Variables

The area of study is a lake district in the municipality of Prespes, which belongs to the prefecture of Florina and is located in the most Northwestern part of the country, bordering Albania and FYROM with which Greece shares the two lakes of Prespes. Within the municipality of Prespes live about 2577 people in 16 villages with the lowest population density in the country of 3 inhabitants/Km^2 (Census, 2011). The primary sector is the main employer in the area with about 370, mostly small and medium family farms, engaged in plant and animal production in a total area of approximately 1150 ha of arable land of which 1000 ha are cultivated with beans. Total bean output varies from 2500 to 3000 tn/year according to weather conditions. 230 farms cultivate the two PGI bean varieties in the designated zone that includes 9 villages.[1] Bean production is concentrated mainly in the 5 villages Laimos, AgiosGermanos,Plati, Kallithea and Lefkona, (65% of cultivated land). Dry beans have been cultivated in the area in a small scale as early as the 1920's but it is the constructionof an irrigationnetwork that begun in the 60's and was completed in the 70's that marked a shiftin the local economyfrom

[1] The PGI dry beans under study are registered under the following names: 'FasoliagiganteselefantesPresponFlorinas' and 'FasoliaplakemegalospermaPresponFlorinas'(Doors, database). The villages within the designated zone are:Microlimni, Karies, Lefkona, Plati,Laimos,AgiosGermanos, AgiosAchillios, Vrontero andKallithea (www.prespes.gr).

self-sufficiency to intensive agriculture. Since the mid1980s, the cultivation of beansis a majorsource of incomefor farmers in Prespes. The particular varieties of PGI beans are of great quality and owe their particular characteristics to the soil and climatic conditions in the area.

The sample used in this study, consisting of 104 bean farms, is collected within the specific area of protected geographical indication and its distribution is presented in figure 1.[2]

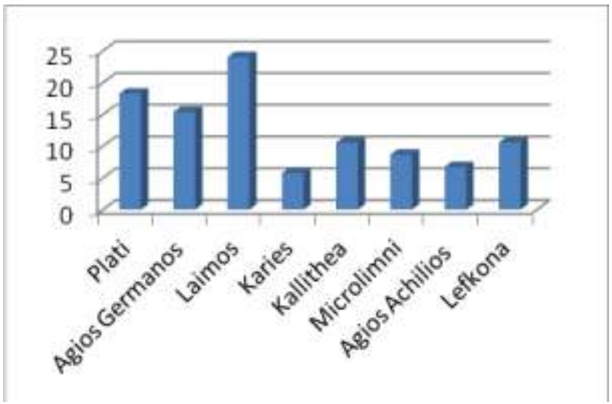

Figure 1. *Spatial Distribution of farms in the sample*

Data were collected by means of a structured questionnaire and with face to face interviews, in 2012-2013. Two researchers visited the area, came across many farmers in the meeting place of each village and completed the questionnaire with those farmers who were willing to cooperate in this research. The majority of producers in the sample are men (83%), married (87%), having a family size with an average of 2.3 adult family members and 0.8 children. The average age in the sample is 50 years with most farmers (53%) being in the age group between 40-60. The percentages of young (less than 40) and older farmers (above 60) are equal, around 23%. The average years of education in the sample are about nine years. Specifically, 24% of farmers have attended six or fewer years in primary school, 33% have high school diploma and 25% of respondents have completed 12 years of education. It is worth noting that about 15% are graduates of a vocational training school and 3% have a higher education. In the sample, 37% has farming experience from 20 to 40 years, 35% are young farmers (less than 20 years), and 29% have long experience in agriculture (more than 40 years). Although the majority comes from a farming family (86.5%) only a little more than half (52%) has agriculture as their main occupation. The part time farmers in the sample earn on average 70% of their income from activities other than agriculture. Bean farming is a monoculture for nearly the whole sample and the average farm size is 6.4 ha, with more than half (55%) farming less than 5 ha, 25% farming up to 10 ha and 21% has large farms with more than 10 ha.

The summary statistics of all variables used for the particular study are shown in Table 1. Nearly all farms in the survey produce only the two types of PDO beans with the exception of three farms, which are also involved in animal breeding. The 'output'

[2] Vrontero does not appear in the sample because there is no bean cultivation in this village.

Table 1. *Descriptive statistics of inputs and outputs*

	Output ('000 €)	Land (ha)	Labor ('000 hours/p.a.)	Fertilizers ('000 €)	Pesticides ('000 €)	Irrigation ('000 €)	Capital ('000 €)
Average	64,5	6,4	2,5	2,6	2,3	1,7	53,1
Minimum	5,6	0,6	0,5	0,3	0,2	0,2	1,0
Maximum	361,4	29,5	7,0	9,9	9,4	8,0	153,0
Median	37,4	4,0	2,1	1,8	1,6	1,1	52,0
Stand. dev.	60,8	5,3	1,6	2,0	1,8	1,4	37,8

variable is measured in terms of total gross revenue from bean farming (in euros), based on collected data for cultivated land, bean yields per stremma (1 stremma = 0.1 ha) and bean market prices. Farmers receive the basic single farm payment and less favoured area compensatory allowance payments, neither of which are added in the output variable. Six inputs are included in the production model, namely 'land' which is measured in stremmas, 'labor' measured in annual working hours, 'fertilizers', 'pesticides', 'irrigation cost' and 'capital stock' all measured in euros. The 'labor' variable includes both family and hired labor with the majority of farms (65 %), however, relying exclusively on family labor. The variable is calculated based on the total number of persons employed in each farm and the reported number of work days for each person. The 'fertilizer' variable is calculated on the basis of recorded quantities, number of applications and prices of basic, surface and foliar fertilizers used by the surveyed farms. The 'pesticide' variable includes the cost of insecticides, fungicides and pesticides and the calculations relied on the quantities used on each farm, the number of applications and the prices of each type of applied agrochemical. The 'irrigation' variable refers to annual irrigation fees paid by each farm to the local water authorities. The 'capital stock' variable includes the replacement value of all types of machinery and buildings that were recorded on each farm in the sample and is expressed in end-of-the-year terms.

4. Results

The frequency distribution of farm technical and scale efficiency scores and the summary efficiency measures, of average efficiency, aggregate efficiency and the performance of the APU are presented in Table 2 and Figure 2. On average, the farms in the sample may increase output by 20% if they eliminate both technical and scale inefficiency. These output gains rarely exceed 40% as the vast majority of farms achieved productive efficiency scores in the range of 0.6 to 1.00.

The arithmetic average and the median are the same for technical efficiency but different for scale efficiency. The median of SE is slightly larger than the mean because its distribution is slightly skewed on the left with fewer farms at lower levels of SE.Small standard deviations show that efficiency values in the data set are close to the mean, on average, but technical efficiency is relatively more heterogeneous than scale efficiency.

Table 2: *Frequency distribution of technical and scale efficiencies*

	Productive efficiency	Technical efficiency	Scale efficiency
Efficiency Score	Number of farms in range		
30-40	1	1	0
40-50	0	0	0
50-60	1	0	0
60-70	18	5	1
70-80	33	30	5
80-90	33	41	9
90-100	12	13	82
No of efficient units	6	14	7
Average	0.794	0.837	0.949
Median	0.795	0.839	0.975
Minimum	0.95	0.398	0.614
Maximum	1	1	1
Standard deviation	0.112	0.104	0.070
APU	0.827	0.837	0.987
Aggregate	0.843	0.862	0.978

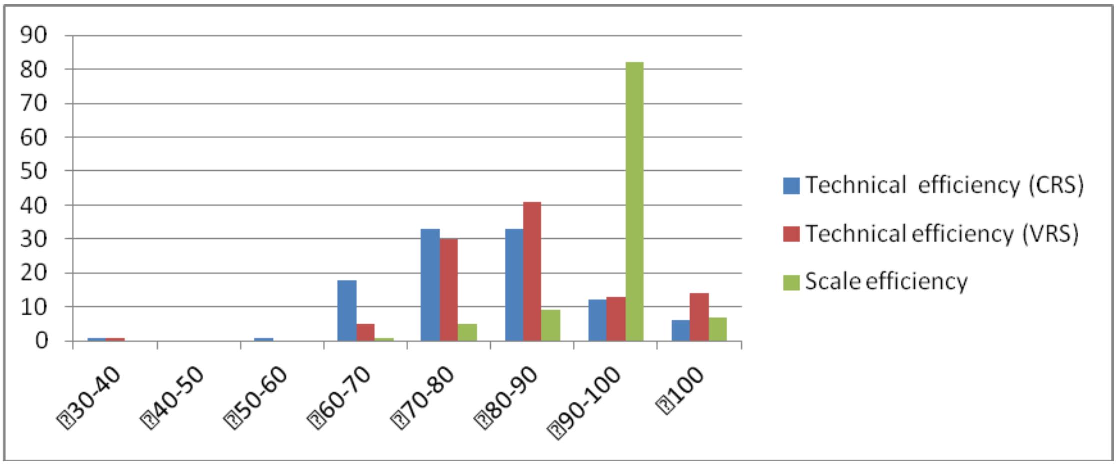

Figure 2 *Efficiency Distributions*

Technical inefficiency is the main source of overall inefficiency rather than scale inefficiency, with corresponding efficiency estimates of 0.837 and 0.949 respectively. This means that the bean farms in the sample produce below the frontier and could raise output by 16% if they had improved on the use of current technology, rather than operate at an inefficient scale. Benchmarking technical efficiency and scale efficiency of the (APU) average production unit (0.827 and 0.987) are greater than average while best practice efficiency of APU is the same as average efficiency (0.837).Aggregate technical efficiency in the benchmark frontier, that is under constant returns to scale (λ_κ non-negative), is greater than efficiency of theAPU which is greater than average efficiency. There are 14 farms in the sample (13%) that are technically efficient of which almost half are both technically and scale efficient.In the context of the best practice frontier, variable returns to scale add 8 more efficient firms two of them with increasing returns to scale (IRS) and six with decreasing returns to scale (DRS). This is expected since more firms are close to the best practice frontier associated with the observed input mix than to the benchmark frontier.The APU scale efficiency is greater than aggregate efficiency, which is greater than average efficiency.

The vast majority of the farms in the sample (87%) operates in a sub-optimal scale exhibiting increasing returns to scale which means that their output is relatively low and can grow further to reach the optimal scale (Table 3). Those farms operating under constant returns to scale (7%) are both technically and scale efficient except one, which is scale efficient but technically inefficient. Farms working in a supra-optimal scale (6%) are more technically and scale efficient than farms working in a sub-optimal scale.

***Table 3**: Technical and scale efficiencies scores of PGI Beans Farms*

	Number of farms	%	Productive efficiency	Technical efficiency	Scale efficiency
Decreasing returns to scale	6	5.77	0.877	0.907	0.967
Constant returns to scale	7	6.73	0.999	0.999	1.000
Increasing returns to scale	91	87,50	0.772	0.820	0.944

According to the results reported in Table 4 all metrics with the exception of the number that an efficient unit appears as a peer indicate the same set of influential peers. There are four of them, three operating with constant returns to scale and one operating with increasing returns to scale. Form the 14 farms found to be efficient according to the best practice, i.e. variable-returns-to-scale, frontier, five are self- evaluators as they do not appear as peers for any inefficient farm and 9 are reference peers. From them, two operate with increasing returns to scale, one with decreasing and six with constant returns to scale. From the most influential, the first one operates with increasing returns to scale and the second one with constant returns to scale. They have however quite different profiles.

Table 5 presents the farms that appear more frequently as peers, in terms of both technical and scale efficiency aspect, in an order from the higher (# 82) to lower frequency (# 77). Farm # 82 is the biggest farm in the sample performing as peer 88 times, while farms # 72 and # 88 appear 64 and 57 times respectively, all producing under constant returns to scale. Farm # 77 is among the smallest farms, operates under increasing returns to scale but is a peer in terms of technical efficiency 77 times, and, becomes second after the best performer. This farm effectively acts as a peer for the very small farms in the sample.

Table 4*: Peer Identification*

Farm Code	Returns to Scale	Number of times as a peer	Number of times with the highest intensity variable	Reference share	Benchmarking share
6	IRS	0	0	0	0
14	IRS	0	0	0	0
20	IRS	0	0	0	0
23	IRS	0	0	0	0
30	IRS	15	5	0.026	0.048
34	CRS	5	0	0	0.002
58	DRS	0	0	0	0
70	CRS	4	0	0.001	0.002
72	CRS	63	17	0.115	0.211
77	IRS	76	51	0.465	0.454
82	CRS	87	11	0.233	0.159
87	DRS	3	0	0	0.001
88	CRS	56	6	0.158	0.121
93	CRS	2	0	0.001	0.003

Table 5*: Characteristics of the most influential peers*

	# 82	# 72	# 88	# 77
Revenue	361375	19200	98488	5632
Land	295	20	80	6
Labour	6425	500	6150	600
Fertilizer	4870	760	3120	262
Pesticides	9420	780	3040	223,5
Capital	116000	1000	132500	15000
Water	8000	300	2200	162
Yield	1225,0	960,0	1231,1	938,7
Labour productivity	56,2	38,4	16,0	9,4
Capital productivity	3,1	19,2	0,7	0,4
Capital labour ratio	18,1	2,0	21,5	25,0
Land fertilizer ratio	16,5	38,0	39,0	43,7
Land pesticides ratio	31,9	39,0	38,0	37,3

The difference between the efficiency of the APU and average efficiency is very small (0,05%) and as results show in Table 6, it is due to low reallocation inefficiency and a covariance term between size and efficiency that may be non-zero but is small.in magnitude. As can be seen in Table 6, the extent of reallocation efficiency is higher than that of technical and scale efficienciesand so bigger gains can be expected from improving farm performance by mainly using in a more efficient manner the existing inputs and/or adjusting towards the optimal scale than from reallocating inputs across the sample farms. In addition, the covariance term is positive and specifies that output is proportionally located at high or low efficiency farms.

Table 6: *Structural, Aggregate and Average Efficiency*

Efficiency of the APU	0.8370
Reallocation Efficiency	0.9717
Aggregate Efficiency	0.8618
Average Efficiency	0.8374
Covariance Term	0.024

Table 7*: Analysis of the covariance term*

	S-Smean<0		S-Smean=0		S-Smean>0			
	farms	%			farms	%	Total	%
F-Fmean<0	38	36,5	4	3,8	9	8,7	51	49
F-Fmean=0	0	0	0	0	0	0	0	0
F-Fmean>0	22	21,2	2	1,9	29	27,9	53	51
Total	60	57,7	6	5,8	38	36,5	104	100

The covariance term is further analysed in Table 7 where farms are classified according to their size and technical efficiency scores. The covariance term is positive if farms with a higher than average efficiency also have a larger than average output share and farms with lower than average efficiency also have a smaller than average output share. In this particular case, where the covariance term takes a value of 0.0244, more than half of the farms (55%) with efficiency scores above average are larger farms. Similarly, within the group of relatively inefficient farms, with efficiency scores below average, the majority (74%) are smaller farms.

Concluding Remarks

Our main findings are summarized as follows: (a) technical rather than scale efficiency seems to be the main source of productive inefficiency. Thus on average more output gains may be realized by moving closer to the best practice frontier rather than moving towards to the optimal scale. (b) The vast majority of farms operate in a sub-optimal scale and thus their output is relatively low compared to optimal scale. (c) Farms operating with supra-optimal scale (DRS) are more scale and technically efficient than farms operating with sub-optimal scale (IRS). (d) Only minimal gains in aggregate output may be achieved by reallocating resources among the sample farms as the extent of reallocation inefficiency is rather small (3%). (e) There is a positive relationship between farm size and technical efficiency

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