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Productive Efficiency of Subsidized Organic Alfalfa Farms

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This paper assesses the efficiency and performance of organic alfalfa farms. Data were obtained from questionnaires collected from forty farms participating in an EU-subsidized program promoting the switch to organic farming. Results obtained using the bootstrap Data Envelopment Analysis methodology show that larger farms had lower yields and lower efficiency scores and more experienced farmers had higher efficiency scores. A Tobit analysis of the impact of environmental factors and subsidies on farm efficiency demonstrates that CAP subsidies cause perverse incentives, raising questions about the efficiency of such policies for sustainable agricultural development.

Key words: bootstrap DEA, CAP subsidies, organic alfalfa farming, sustainable agricultural development, technical efficiency

Introduction

In most EU countries, livestock production accounts for one third to one half of total agricultural output. The cultivation of animal feed is an important sub-sector of agriculture that meets the needs of livestock producers. Alfalfa grown in Western Greece is one of the most important crops used as animal feed in Greece: 3.7% of Greek agricultural land—137,600 hectares (ha)—is devoted to alfalfa cultivation, and annual production is estimated at 1,393,000 tons (Greek Ministry of Agriculture, 2007). Since 1999, subsidies provided by the EU Common Agricultural Policy (CAP) have helped to promote a switch to organic alfalfa at the national level. These subsidies provide significant financial incentives for farmers to switch their production to organic farming. However, given the recent economic crisis, added pressure is being exerted to use public funds more productively and efficiently. These pressures raise questions about the efficiency and performance of CAP subsidized organic alfalfa farms and the effects the subsidies have on efficiency scores.

We use the bootstrap Data Envelopment Analysis (DEA) methodology developed by Simar and Wilson (1998) to estimate farm efficiency scores. The bootstrap methodology is a straightforward way to analyze the sensitivity of efficiency scores relative to the sampling variations of the estimated frontier and provides a statistical basis for nonparametric efficiency measures. This study estimates the productive efficiency of organic alfalfa farmers in Greece.

Materials and Methods

Bootstrap Data Envelopment Analysis

The economic theory on which efficiency analysis is based derives from Koopmans (1951) and Debreu's (1951) seminal work on activity analysis. The Data Envelopment Analysis (DEA)

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approach was introduced by Farrell (1957), whose study is the first empirical work to address the problem of measuring efficiencies for a set of decision making units (DMUs). Charnes, Cooper, and Rhodes (1978) later operationalized the DEA methodology in terms of linear programming.

We develop the DEA approach and bootstrap estimation, following notation introduced by Simar and Wilson (2000). The activity of DMUs is constrained by the production set Ψ of feasible points (x,y) as:

(1) $$\Psi = \{(x,y) \in \mathbb{R}_{+}^{p+q} | x \quad \text{can produce} \quad y\},$$

where $x \in \mathbb{R}_{+}^{p}$ is an input vector and $y \in \mathbb{R}_{+}^{q}$ is an output vector. The DEA methodology assumes that Ψ is convex and the attainable set may be estimated by:

(2) $$\hat{\Psi}_{DEA}(\chi_n) = \{(x,y) \in \mathbb{R}_{+}^{p+q} \mid y \leq \sum_{i=1}^{n} \gamma_i y_i, x \geq \sum_{i=1}^{n} \gamma_i x_i, \sum_{i=1}^{n} \gamma_i = 1, \gamma_i \geq 0 \forall i = 1,2,\ldots,n\}$$

of the sample observations in χ_n. Efficiency corresponding to a given point x_0, y_0 is then estimated relative to the $\hat{\Psi}_{DEA}$ boundary as:

(3) $$\hat{\theta}_{DEA}(x_0,y_0) = \inf\{\theta | (\theta x_0, y_0) \in \hat{\Psi}_{DEA}(\chi_n)\}.$$

Kneip, Park, and Simar (1998) derived analytic results for the consistency of the DEA estimator. In addition, Gijbels et al. (1999) obtained asymptotic sampling distributions, albeit only for the univariate framework. Given that the asymptotic results only apply in the univariate case, Simar and Wilson (1998) proposed an algorithm that implements the bootstrap to frontier estimation. The algorithm provides an approximation of the sampling distribution of $\hat{\theta}_{DEA}(x,y) - \theta(x,y)$ in the multivariate case and allows confidence intervals to be obtained for $\theta(x,y)$. This approach allows statistical inference when using the DEA approach in non-parametric frontier models.

Measurement Error Identification

We first employ the methodology developed by Wilson (1993) to identify observations that may contain some form of measurement error. This step is necessary because the efficiency scores produced by DEA methods (as well as other linear programming-based models like the deterministic parametric models proposed by Lovell and Sickles (1983) and others) may be severely influenced by the presence of outliers in the data. Outliers are the result of recording or measurement errors and should be corrected if possible or else deleted from the data. In the case of DEA, since the frontier is nonparametric, diagnostics based on parameter estimation cannot be employed. The statistic developed by Wilson (1993) is an extension of the one developed by Andrews and Pregibon (1978) for the case of multiple outputs and is most commonly based on graphical analysis.

First, some notational definitions are needed. For a value ξ computed from a set of observations $S = \{1,\ldots,n\}$, let $D_L^{(i)}\xi$ denote the value computed similarly from observations in the set $S - L$, where $L \subset S$ and L contains i elements, $i < n$. More specifically, the statistics defined by Andrews and Pregibon (1978) and by Wilson (1993) are:

(4) $$R_L^{(i)}(\boldsymbol{X}^*) \equiv \left[D_L^{(i)}\left(\left|\boldsymbol{X}^{*\prime}\boldsymbol{X}\right|\right)\right]\left|\boldsymbol{X}^{*\prime}\boldsymbol{X}\right|^{-1},$$

where $\boldsymbol{X}^* = [X'Y]$, $\boldsymbol{X}$ is an $(n \times K)$ matrix of inputs including a column of ones, $\boldsymbol{Y}$ is an $(n \times 1)$ matrix of the one output, for each of the n firms, each of which uses $K - 1$ inputs to produce the one output, and $D(|\dot{|})$ is the determinant of the matrix $\boldsymbol{D}(\dot{})$. This statistic represents the proportion of the geometric volume in K space spanned by a subset of the data obtained by deleting i observations relative to the volume spanned by the entire data set. Sets of observations L deleted from the sample that produce small values of $R_L^{(i)}$ are then considered to be outliers in the real sense. Andrews and

Pregibon (1978) recommend computing $R_L^{(i)}$ for $i = 1, 2, \ldots, n$ to avoid the problem that would occur if two or more points lie near each other in K space but lie far from other observations in the data. They suggested a graphical analysis in which the log ratios $\log[R_L^{(i)}(\boldsymbol{X}^*)/R_{\min}^{(i)}]$ $(i = 1, \ldots, i_{\max})$ are computed for the subsets, with the largest values $q_l^* q_l^{*'}$, where q_l^* is the lth row of Q^*, $\boldsymbol{X}^* = Q^* R^*$, $i_{\max}$ is the largest subset to be deleted, and $R_{\min}^{(i)}$ is the minimum ratio. Examining the separation between the smallest ratios indicates possible outliers. The results of the outlier detection analysis are presented below.

Data and Descriptive Statistics

Data were collected from the Prefecture of Kozani, Western Macedonia, Greece, in 2008, when sixty-five farms participated in the EU-subsidized program promoting organic farming. Forty of those farms cultivated alfalfa as the only organic crop and were selected because of their crop homogeneity. Farmers either fully (on all crops and all plots) or partially adopted organic farming and were subsidized for land plots converted to organic farming with a per hectare payment of 600€. On average, subsidies amounted to 12,550€ per farm, about 12% of agricultural output value.

As part of the program, farmers were required to fill out questionnaires that included information about farmers' sociodemographic characteristics and detailed accounting records for the organic farming portion of the farming activities. Thus, reported capital, land, labor, and variable input expenditures were calculated either by direct values reported by the farmers (for land, labor, and variable inputs) or by apportioning costs for capital inputs of partial adopters. In addition, information was collected about each farmer's experience with organic farming, reasons for converting to organic farming, and whether they were full or partial adopters of organic farming and full or part-time farmers.

The average farm had an output valued at approximately 128,000€, while employing approximately 85,000€ capital, 20,000€ of variable inputs; 295 workdays were used to farm 2.2 ha of land (table 1). In addition, table 1 reports descriptive statistics for the sub-samples of partial and full organic farming adopters. The sample consists of thirteen partial adopters and twenty-five full adopters. The descriptive statistics show that full adopters employ more of all inputs. More specifically, on average full adopters employ 30% more capital, 54% more land, 19% more labor and 32% more variable inputs to produce 18% more output, compared to partial adopters. A farmer's status as a full or partial adopter of organic farming may therefore explain differences in efficiency. In addition, substantial variation in all measured variables exists among the sample farms. Output varied from 5000€ to 630,000€, capital employed on the farm varied from 0€ to 500,000€, land cultivated varied from 0.14 ha to 18 ha, and labor employed varied from 22 workdays per year to 1980 workdays per year. The substantial variation among the representative sample of farms allows us to examine whether or not organic alfalfa production exhibits constant returns to scale and, furthermore, to determine optimal farm size based on estimated efficiency scores. In addition, it should be noted that a number of farms reported zero use of capital inputs. These farms rent all necessary farming equipment, or, more often, hire foreign labor and equipment to perform all cultivation tasks; they are therefore not missing values.

Results and Discussion

Outlier Detection

Following Wilson (1993), the outlier detection analysis reported values of $R_{\min}^{(i)}$ for $i = 1, \ldots, 12$, and are presented in table 2. $R_{\min}^{(i)}$ was found by computing all values for $R_L^{(i)}(\boldsymbol{X}^*$ and then compared to

Table 1: Descriptive Statistics

	Mean	**Std. Dev.**	**Min**	**Max**
Full sample				
Output (in €)	127,198.43	155,839.40	5,000.00	63,0000.00
Capital (in €)	84,926.99	94,911.68	0.00	500,000.00
Land (in ha)	2.19	3.25	0.14	18.00
Labor (in workdays)	294.21	393.62	22.19	1,980.00
Variable Inputs (in €)	19,722.78	21,515.06	928.56	103,362.00
Partial adopters		.		
Output (in €)	118,215.80	161,935.20	5,000.00	630,000.00
Capital (in €)	74,519.49	81,159.63	7,797.43	266,095.90
Land (in ha)	1.66	2.07	0.14	10.50
Labor (in workdays)	267.88	438.07	22.19	1,701.00
Variable Inputs (in €)	16,640.10	24,448.99	928.56	96,388.5
Full adopters		.		
Output (in €)	139,839.30	159,041.20	11,060.00	600,000.00
Capital (in €)	97,133.05	102,615.80	5,000.00	500,000.00
Land (in ha)	2.58	3.61	0.16	18.00
Labor (in workdays)	320.22	390.82	25.59	1,980.00
Variable Inputs (in €)	22,077.79	20,854.19	1,115.48	103,362.00

Table 2: Outliers

i				**Observations**				
1	38							
2	22	23						
3	22	23	38					
4	31	22	23	38				
5	31	30	22	23	38			
6	31	30	28	22	23	38		
7	31	30	29	28	22	23	38	
8	31	30	40	29	28	22	23	38

the value obtained by computing the $\begin{pmatrix} 2i_{\max} \\ i \end{pmatrix}$ subsets with the largest values of $R_L^{(i)}(\boldsymbol{X}^*)$ from the subset of observations, described above. For each $i = 1, \ldots, n$, figure 1 displays the 17 smallest values of the log ratios $\log[R_L^{(i)}(\boldsymbol{X}^*)/R_{\min}^{(i)}]$ computed for the $\begin{pmatrix} 16 \\ i \end{pmatrix}$ subsets with the largest values $q_l^* q_l^{*'}$, where a line connects the second smallest values for each i to illustrate the separation between the smallest rations for each i (Wilson, 1993). For $i = 2$, the separation is relatively large, with a log ratio larger than 1. Observations 22 and 23 listed for $i = 2$ in table 2 are regarded as outliers. Looking more closely at observations 22 and 23, we note that these are very small-scale farms with less than 0.7 ha of land and zero values for capital. As mentioned earlier, a number of farms in the sample report zero capital, since they rent all necessary equipment or have others perform required tasks for them. These expenses appear in variable inputs. Therefore, we proceed with a reduced sample of 38 observations to perform the DEA bootstrapping efficiency analysis.

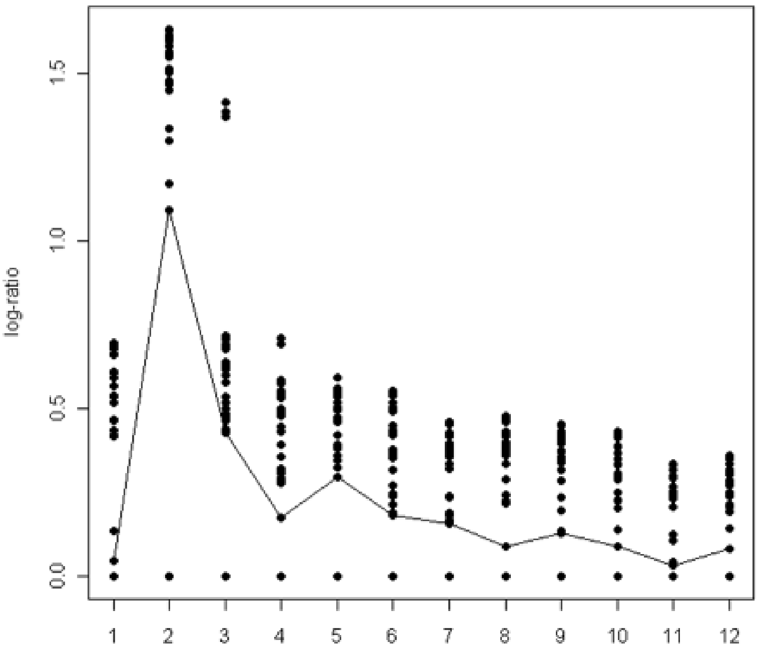

Figure 1: Log-Ratio Outliers Plot

Table 3: Distribution of Technical and Scale Efficiencies

	Technical efficiency		Scale efficiency	
Efficiency Score	**Number of DMUs**	**%**	**Number of DMUs**	**%**
0.0-0.19	4	10.5	1	2.6
0.2-0.39	6	15.7	1	2.6
0.4-0.59	9	23.7	4	10.5
0.6-0.79	16	42.1	11	28.9
0.8-1.00	3	8.0	21	55.4

Notes: Efficiencies are estimated from the bootstrap DEA. Technical efficiency is estimated under Variable Returns to Scale.

Technical and Scale Efficiency

Table 3 includes results obtained using the bootstrap method introduced by Simar and Wilson (1998) and the input-oriented DEA. Three farms are best-practice (technical efficiency scores of over 0.8) and half of the sample's farms have a technical efficiency score above 0.6. Mean Technical Efficiency under VRS is 0.664 (0.544 after the bootstrap correction), implying that farms could reduce their inputs, on average, by 33.4% (45.6%) to produce the same level of output and that considerable variation exists among alfalfa farmers in the region.

The interpretation of the scale efficiency scores, with mean scale efficiency after the bootstrap correction of 0.776, implies that the average farm size is very close to optimal, since only an additional 22.4% productivity gain is feasible, assuming no other constraining factors, if farms are scaled to optimal size.

The classification of alfalfa farms by size shows that on average, small farms (less than 1 ha) are more technically efficient than medium-size and large farms (table 4). Small and large farms are equally scale efficient, with medium-size farms being more scale efficient, as their average

Table 4: Average Efficiency Scores by Size, Experience, and Degree of Organic Farming Adoption

	TE CRS	TE VRS	SE	% of DMUs
Overall sample mean	0.42	0.54	0.78	
Classification by size				
Less than 1 ha	0.48	0.67	0.72	39.47
1-2 ha	0.37	0.44	0.80	34.21
More than 2 ha	0.40	0.49	0.83	26.32
Classification by organic farming experience				
Before 2005	0.40	0.56	0.82	36.84
2005-2006	0.46	0.53	0.75	63.16
Classification by degree of organic farming adoption				
Partial adopter	0.41	0.59	0.70	34.21
Full adopter	0.50	0.57	0.85	65.79

Notes: TE CRS: Technical efficiency under Constant Returns to Scale. TE VRS: Technical efficiency under Variable Returns to Scale. SE: Scale Efficiency. DMU: Decision making unit. The bootstrap DEA approach was used to make inference of efficiency estimates.

size is only 2.5% away from optimum. Explaining why small farms are more technically efficient (0.479 and 0.670) requires an examination of farmers' organic farming experience. Efficiency scores for farmers with more organic farming experience are substantially higher than for other farmers (table 4). Farmers who began organic farming prior to 2005 (37% of sample) have mean technical efficiency scores of 0.401 (CRS) and 0.563 (VRS) and scale efficiency scores of 0.819. Farmers with only one or two years of organic farming experience (63% of sample) have mean technical efficiency scores of 0.455 (CRS) and 0.534 (VRS) and scale efficiency scores of 0.750. The average farm size for older organic farmers (prior to 2005) is 1.15 ha, whereas the average farm size for newer organic farmers (after 2005) is 2.74 ha, which may explain why small-scale farmers appear to be more technically efficient than medium- and large-scale farmers. Finally, whether farmers decide to partially or fully adopt organic farming may explain some of efficiency differences. The classification of efficiency scores based on whether farmers partially or fully adopt organic farming indicates that full adopters have higher technical efficiency and scale efficiency scores than partial adopters. However, the independent samples t-test indicated that for all the efficiency measures employed, the two sub-samples cannot be statistically distinguished at the 5% significance level.

The most notable feature of DEA is that it is possible obtain information and evidence for a managerial evaluation of each individual DMU, thereby identifying and assessing the exact sources of inefficiencies for each unit (Galanopoulos et al., 2006). This process facilitates the determination of where the greatest gains can be made from improvements in efficiency (Abbott and Doucouliagos, 2003). The analysis is performed here for the least technically efficient farm, DMU 4. For this analysis we examine the VRS DEA efficiency score (pure technical efficiency), since the assumption of constant returns to scale is only appropriate when all DMUs are operating at an optimal scale. The results of the analysis for the sample do not support this argument, as only a small fraction of the farms in the sample are optimally sized.

The TE VRS for DMU 4 is 0.096, implying that the farm could become technically efficient (under the Farrell definition) if all inputs are reduced proportionally by 90.4% (table 5). In addition, slack movements and the projected point for DMU 4 are reported in table 4. More specifically, capital use can be reduced by 484,160.58€ (96.8%), land by 0.28 ha (8.7%), labor by 406.21 days/year (90.2%), and variable inputs by 28,522.02€ (90.7%) and the farm can still produce the same output level. It should be noted that this DMU is a full adopter and therefore produces only organic alfalfa.

Table 5: Actual and Efficient Input Use Levels of DMU 4

	Inputs			
	Capital (€)	**Land (ha)**	**Labor (Days/year)**	**Variable Inputs (€)**
Actual values	500,000.00	3.20	450.00	31,438.00
Radial movement	−451,350.00	−0.28	−406.21	−28,379.00
Slack movement	−32,810.58	0.00	0.00	−142.94
Projected change	−484,160.58	−0.28	−406.21	−28,522.02
Projected point	15,839.42	0.32	43.79	2,915.98

There are several plausible explanations for the DMU's low efficiency score. However, given the available information, it is impossible to fully explain the results, other than reporting that the farm owner is a 44 year old, male high-school graduate who recently converted the operation to organic farming. However, in Greece farmers are often observed to over-invest in capital due to capital equipment's role as "status symbols" in local communities. The excess capacity serves no purpose other than to convey the farmers' status, even if it is inefficient.

Eight farms are purely technically efficient; that is, they operate on the production possibilities frontier. The eight pure technically efficient DMUs employ 79,188.54€ of capital, 2,86 ha of land, 372,4 workdays per year, and 25,743€ of variable inputs to produce 233,633€ of output. The preceding analysis may provide farmers with useful information in determining excessive input use and provides the basis for managerial actions that can improve farm efficiency. However, DEA can neither fully explain the underlying differences in efficiencies in the use of a single input nor assess the constraints that limit changes in operational practices that would otherwise improve efficiency (Galanopoulos et al., 2006). Thus, given the limitations of the information provided by DEA, it should only be considered as the starting point for a farmer seeking to improve their farm production system.

Assessment of Environmental Impact on Farm Efficiency

We regress the estimated efficiency scores on a set of explanatory variables, paying particular attention to the role of subsidies and sociodemographic and managerial characteristics and investigating the extent to which they influence the efficiency of an organic alfalfa farm. The regressors are the farmer's age (*Age*), years of school (*School*), household size (*Hhd*), years of experience in organic farming (*OrgExp*), whether they are full-time farmers (*FullTime*), whether they became organic farmers due to concern for the environment (*Env*) (as opposed to the economic incentives offered), and the ratio of subsidies to output (S/Y).

The dependent variable (inefficiency scores) takes values in the unit interval. Hence, a Tobit with lower limits at zero and upper limits at one is an appropriate regression model (Sharma, Leung, and Zaleski, 1999; Tauer and Stefanides, 1998). The Tobit specification is defined as:

$$(5) \qquad y_i^* = x_i\beta + u_i \quad \text{with the observed } y \text{ given by:} \quad y_i = \begin{cases} 0 & if \quad y_i^* \leq 0 \\ y_i^* & if \quad 0 \leq y_i^* \leq 1 \\ 1 & if \quad y_i^* > 1 \end{cases},$$

where y_i^* is the latent variable, x_i denotes the vector of explanatory variables, β denotes the parameters to be estimated, and u_i is an i.i.d. random error term. The results of the Tobit analysis are based on the VRS efficiency scores and so bootstrapped confidence intervals are employed to help correct for heteroskedasticity, since ignoring heteroskedasticity can lead to inconsistent estimates.[1] It should be noted that the estimated coefficients in a Tobit regression model do not have a direct

[1] We thank an anonymous referee for this suggestion.

Table 6: Tobit Regression Results (N=38)

Variable	Coefficient	Std. Error
Age	0.02^{**}	0.01
School	0.01	0.02
Hhd	−0.05	0.09
OrgExp	−0.01	0.01
FullTime	-0.28^{**}	0.15
Env	-0.17^{*}	0.10
S/Y	-0.49^{***}	0.42
Constant	0.67	0.55

Notes: Log-likelihood=-9.46, Prob>chi2=0.047, Pseudo R2=0.57. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5% and 1% level.

interpretation as a true marginal effect, but as a two-scale effect: first, an effect on the mean of the dependent variable, given that it is observed, and second, an effect on the probability of the dependent variable being observed. Therefore, we report marginal effects calculated at the mean of the data.

The regression results show that the farmer's age and full-time employment status are statistically significant positive determinants of the pure technical efficiency score, implying that older farmers and full-time farmers are more efficient. Furthermore, farmers who indicate that they switched to organic farming purely for ecological reasons are statistically significantly less likely to be technically efficient; that is, farmers with ecological rather than financial motives for switching to organic farming are less efficient (table 6). More importantly, the effect of subsidies on farm efficiency is negative and statistically significant. The marginal effect of a 1% increase in the ratio of subsidies to farm output decreases a farm's pure technical efficiency score by 1%. This finding provides evidence that subsidies either work as a disincentive for farmers to manage their operations efficiently or attract less efficient farmers into the activity, since either way they are compensated for their reduced efficiency through CAP subsidies.

Conclusions

We estimate the production efficiency of individual organic alfalfa farmers in Greece by employing the Simar and Wilson bootstrap Data Envelopment Analysis methodology and then examine the effect of farm size and farmer experience on productive efficiency. The results indicate that smaller farms and farmers who have more experience with organic alfalfa farming are more technically efficient.

More interestingly, an assessment of the impact of CAP subsidies on pure technical efficiency revealed that, on average, a given percentage increase in the ratio of subsidies to farm output decreases the pure technical efficiency score by the same percentage. This finding highlights the perverse incentive effects of subsidies and raises serious doubts about the efficiency of such policies, both in terms of their impact on farm-level efficiency and on sustainable agricultural development at the macro level.

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