CONDITIONAL EFFICIENCY ESTIMATION WITH ENVIRONMENTAL VARIABLES: EVIDENCE FROM GREEK CEREAL FARMS

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***Abstract**: The objective of this paper is to assess technical efficiency of cereal production in Greece in a nonparametric framework while accounting for a set of exogenous variables. To this end, we implement robust partial frontier techniques on a sample of cereal-producing farms included in the Farm Accountancy Data Network (FADN). Moreover, we assess the partial impacts of the environmental variables using non parametric regression tools.*

***Keywords**: Nonparametric estimation, conditional efficiency, cereal farms*

JEL Classification Codes: D24, Q12

1. INTRODUCTION

The assessment of technical efficiency provides information to managers and to policy makers about differences in performance among production units and the potential for improvements. Over the last 40 years the research on this important topic has evolved largely around two alternative approaches, namely, the deterministic and the stochastic frontier models. The latter allow for random noise and, as a consequence, for some observations to lie outside the production set; the former assume that all observations belong to the production set with probability equal to 1. The stochastic frontier models require parametric restrictions on the shape of the production frontier (benchmark) and on the underlying data generation process (e.g. Stevenson, 1980; Battese and Coelli, 1988). Therefore, they lack robustness in cases where the functional form of the frontier and/or the error structure is not correctly specified. The estimation of deterministic frontier models has been, until recently, pursued through envelopment techniques such as the DEA (Charnes et al., 1978) and the FDH (Deprins, et al. 1984) that are quite appealing because they rely on very few assumptions. They are, however, by construction very sensitive to outliers or to atypical observations. This is certainly an important problem when one is interesting in assessing technical efficiency of production units in economic activities where the amount of output is subject to random shocks. In farming, for example, the level of realized output can be quite different from the planned one because of weather conditions and pest attacks.

During the last decade considerable research effort has been devoted to the development of robust non parametric efficiency estimators. These estimators rely on partial frontiers which do not envelop all data points. As such, the partial frontiers provide less extreme surfaces to benchmark individual units and, thus, they are more robust to extreme observations compared to the full frontiers. The robust efficiency estimators have the same asymptotic properties of the FDH and the DEA estimators, the same Weibull distribution, but they attain better convergence rates (e.g. Daraio and Simar, 2007; Aragon et al., 2005; Cazals et al., 2002).

It is well recognized that efficiency estimates which do not account for the operational environment have only a limited value. Therefore, if the individual units in a given sample are influenced by environmental/exogenous factors the efficiency analysis should control for this heterogeneity (e.g. Daraio and Simar, 2005; De Witte and Kortelainen, 2008). The partial frontiers are based on a probabilistic formulation of the production process and they incorporate the operating environment in a very natural way (that is, by conditioning on the exogenous environment). The so-called conditional efficiency approach generalizes previous models and allows a researcher to investigate the impact of environmental variables on the distribution of inefficiencies.

The robust non parametric efficiency estimators have been applied to banking, mutual funds, post offices, and education (e.g. Blass Staub and da Silva e Souza, 2007; Daraio and Simar, 2005, 2006; Daouia and Simar, 2007; Cazals et. al., 2008; de Witte and Kortelainen, 2008). It appears, however, that there have been so far no applications to the agricultural sector. This is disconcerting since the approaches relying on partial frontiers are very suitable for measuring efficiency in the presence of random shocks.

In this context, the present work relies on the robust non parametric order-m estimator to assess efficiency in a sample of cereal farms in Greece. In what follows section 2 presents the analytical framework (unconditional and conditional order-m efficiency measures, and influence of the operational environment). Section 3 presents the data and the empirical results. We note that there is a number of earlier works on efficiency of cereal farms in Greece and in other parts of the World. It is, therefore, interesting to compare their results to those from the robust non parametric order-m estimator (especially with respect to the influence of certain environmental factors on efficiency). Section 4 offers conclusions.

2. ANALYTICAL FRAMEWORK

2.1 The Unconditional Order-m Efficiency Estimator

Let $X \in R_+^p$ be the vector of inputs and $Y \in R_+^q$ be the vector of outputs from a given production process. Let also Ψ be the production set (that means, the set of all feasible input-output combinations) for that process where Ψ satisfies the assumption of free disposability (e.g. Deprins et al, 1984). As noted by Cazals et al. (2002) and Daraio and Simar (2005) the data generating process (GDP) of the random variable (X, Y) can be completely characterized by the knowledge of the probability function

$$(1) \quad H_{XY}(x, y) = prob(Y \geq y, X \leq x)$$

giving the probability that a decision making unit (DMU) that operates at level (x, y) to be dominated; the support of H_{XY} is the production set Ψ. Relation (1) can be expressed as

$$(2) \quad H_{XY}(x, y) = prob(Y \geq y \mid X \leq x) prob(X \leq x) = S_{Y|X}(y|x) F_X(x)$$

where $S_{Y|X}(y|x)$ stands for the (non standard) conditional survival function of Y and $F_X(x)$ for the distribution function of X.

The traditional non parametric efficiency estimators are deterministic in nature since they assume that $prob((x, y) \in \Psi) = 1$ (meaning that all observations belong to the production set). As such, they are sensitive to outliers that can heavily influence estimates of the upper boundary of the support of $S_{Y|X}(y|x)$. To address this problem for the output-oriented efficiency Cazals et al. (2002) suggested to consider, instead of the maximum output levels for given input levels, the expected values of m random variables $Y_i, i = 1,2,...,m$ generated by the q-variate conditional survival function $S_{Y|X}(y|x)$. Thus, instead of considering the full frontier, one draws a partial frontier depending on a random set of m variables consuming, at most, x resources. The partial frontier generated in this way is a less extreme benchmark (it is less likely to be influenced by outliers) relative to full frontier of the deterministic non parametric efficiency estimators.[1] The order-m output efficiency measure is defined as

$$(3)\quad \lambda_m(x,y)=\int_0^{\infty}[1-(1-S_{Y|X}(uy|x))^m]du,$$

where u is a dummy of integration. The estimator of $\lambda_m(x,y)$ from a sample of n observations, denoted as $\hat{\lambda}_m(x,y)$, is obtained by replacing $S_{Y|X}(y|x)$ in (2) by its empirical analog

$$(4)\quad \hat{S}_{Y|X,n}(y|x)=\frac{\hat{H}_{YX,n}(x,y)}{\hat{H}_{YX,n}(x,0)}$$

In (4) $\hat{H}_{YX,n}=\dfrac{\sum_{i=1}^{n} I(x_i\le x, y_i\ge y)}{n}$ is the estimator of the probability function H_{YX} with $I(.)$ being an indicator function.

When the output-efficiency score is $\hat{\lambda}_m(x,y)=1$, the unit in question lies on the robust partial order-m frontier; when $\hat{\lambda}_m(x,y)>1$ an increase in all outputs by $(\hat{\lambda}_m-1)100\%$ is required in order the decision making unit to be located at the order-m frontier; when $\hat{\lambda}_m(x,y)<1$ the unit is classified as "super-efficient" (it is located above the order-m frontier). Note that the order m efficiency estimator is $\sqrt{n}-$consistent (it converges to its true value as quickly as the parametric efficiency estimators). Cazals et al. (2002) show that as $m\to\infty$ the order-m efficiency estimator converges to the FDH output efficient frontier. Nevertheless, even for large finite values of m the two estimators are different, with the order-m estimator being less sensitive to outliers and to atypical observations compared to the FDH estimator.

2.2. The Conditional Order-m Efficiency Estimator

Let $Z\in R^r$ a vector of environmental variables which, although exogenous, they may influence the probabilistic production process. To account for the operational environment in efficiency estimation with robust partial order-m frontiers Cazals et al. (2002) and Daraio and Simar (2005) considered the GDP of the random variable (X,Y,Z) and focused on the conditional distribution of (X,Y) for a given value of Z

$$(5)\quad H_{XY|Z}(x,y\mid z)=prob(Y\ge y, X\le x|Z=z)=S_{Y|X,Z}(y|x,z)F_{X|Z}(x|z)$$

giving the probability that the unit (x,y) will be dominated by other units facing exactly the same operational environment; the support of $H_{XY|Z}$ is denoted by Ψ^Z (a set possibly different from the production set Ψ). As in sub-section 2.1 one can draw m random variables Y_i, $i=1,2...,m$ (with $X\le x$ and $Z=z$) to obtain the relevant partial frontier. The corresponding conditional order-m output-efficiency measure is

[1] In the limiting case with q=1, the partial frontier is the expected output function of order m denoted by $f_m=E(\max(Y^1,Y^2,...,Y^m)|X\le x)$.

$$(6) \quad \lambda_m(x, y|z) = \int_0^{\infty} [1-(1-S_{Y|X,Z}(uy|x,z))^m]du$$

The individual conditional efficiency measure $\lambda_m(x, y|z)$ has the usual interpretation (that is, $(1-\lambda_m(x, y|z))100\%$ stands for the radial feasible change in all outputs a unit operating at (x, y) should perform to reach the efficient boundary of the set Ψ^z).
The non parametric estimator of the survival function in (6) must be obtained using smoothing techniques on z (because of the equality constrain $Z = z$). In particular, the estimator is computed as

$$(7) \quad \hat{S}_{Y|X,Z,n}(y|x,z) = \frac{\sum_{i=1}^{n} I(x_i \le x, y_i \ge y)k_h(z, z_i)}{\sum_{i=1}^{n} I(x_i \le x)k_h(z, z_i)},$$

where k_h is a kernel and h is an appropriate bandwidth. The conditional order-m efficiency estimator $\hat{\lambda}_m(x, y|z)$ then follows by plugging $\hat{S}_{Y|X,Z,n}(y|x,z)$ from (7) into (6).

2.3. Global Separability and Assessment of Impacts of Environmental Variables

The vector of environmental factors Z may either affect the range of attainable values of (X,Y), including the shape of the production set, or it may only affect the distribution of inefficiencies inside a set with boundaries not depending on Z (meaning that only the probability of being less or more far from the efficient frontier may depend on Z) or both (Badin et al., 2010). A given vector of environmental factors $Z = z$ is associated with a different conditional distribution $H_{XY|Z}$ which is in turn associated with a different support Ψ^Z. Under separability, the environmental factors have no influence whatsoever on the support of H_{XY} and it is the case that $\Psi^Z = \Psi$ for every $z \in Z$. If the separability condition is verified, the only potential remaining impact of the environmental factors on the production process may be on the distribution of the efficiencies. Daraio et al. (2010) propose a global test of separability which is based on the distance between two efficient boundaries (namely one with support Ψ and the other with support Ψ^Z). The null hypothesis for the global separability test is $\Psi^Z = \Psi$ for every $z \in Z$ and its complementary that there is $z \in Z$ such that $\Psi^Z \ne \Psi$. The test statistic for a sample of size n is

$$(8) \quad \hat{\tau}_n = \frac{\sum_{i=1}^{n} (\hat{D}'_{FDH,i,n})(\hat{D}_{FDH,i,n})}{n} \ge 0,$$

where $\hat{D}_{FDH,i,n} = Y_i(\hat{\lambda}_{FDH,i,n}(X_i, Y_i) - \hat{\lambda}_{FDH,i,n}(X_i, Y_i|Z_i))$ and $\hat{\lambda}_{FDH}$ is FDH efficiency estimator based on the full frontier. The null is rejected for "large" values of $\hat{\tau}_n$. The optimal Critical Value for testing global separability can be obtained by a bootstrap procedure proposed by Daraio et al. (2010).
For the purposes of management and policy formulation of critical importance is the sort of impact (favorable or unfavorable) of each individual environmental factor on the performance of production units. This can be assessed using the ratio of the conditional to unconditional order-

m efficiency scores (that means, the ratio of the radial distances from the conditional and the unconditional frontiers, respectively) and non parametric regression techniques. Specifically, Daraio and Simar (2005 and 2007) propose the estimation of the following smooth non parametric regression model

$$(9) \quad R_{m,n,i} = g(z_i) + e_i$$

where

$$(10) \quad R_{m,n,i}(x_i, y_i | z_i) = \frac{\hat{\lambda}_{m,n,i}(x_i, y_i | z_i)}{\hat{\lambda}_{m,n,i}(x_i, y_i)}, \qquad i = 1,2,...,n,$$

g is a conditional smooth mean function, and e_i is the usual error term (with $E(e_i | z_i) = 0$). In the output-oriented efficiency and for a univariate and a continuous Z, a horizontal smoothed regression curve implies that the environmental factor has no influence whatsoever on efficiency; an increasing (decreasing) regression curve implies that efficiency rises (falls) with the amount of Z. When an environmental factor has a favorable impact it can be viewed as substitute input which augments the productivity of the X inputs. In the opposite case, the presence of Z reduces productivity by entailing more of the X inputs per unit of output. It should be noted the impact is not necessarily monotonic for all values of Z. An increasing part of the regression may be followed by a decreasing one (and the opposite). Therefore, the approach allows for the existence of different impacts locally.

With multivariate continuous Z factors, the visualization of individual impacts can be achieved through the so-called partial smooth regression plots where only one such factor at a time is allowed to change and the rest are kept at fixed values; for instance, the rest of the environmental factors are set at the first, the second or the third quartile (e.g. De Witte and Kortelainen, 2008; Daraio and Simar, 2007; Badin et al. 2008).

3. AN EMPIRICAL APPLICATION TO CEREAL FARMS IN GREECE

The empirical analysis in this study relies on a sample of 249 cereal farms in Greece. The relevant information has been obtained from the Farm Accounting Data Network (FADN) of the EU and refers to year 2008. Farm output (Y), which is revenue from the production of cereals, is measured in Euros. The production inputs (X) include: (a) total labor (comprising all family and non family one), measured in working hours; (b) total land under cereals, measured in 100m^2; (c) fertilizers and pesticides, measured in Euros; and (d) other operation costs (seeds, electric power, fuel, depreciation, interest, and miscellaneous), measured in Euros. We note that the vector of X inputs considered here is in line with those used in earlier empirical studies on efficiency of cereal farms in Greece as well as in other countries (e.g. Madau, 2007; Tzouvelekas et al., 2002; Giannakas et al., 2001).

The environmental factors (Z) include: (a) the age of the farm owner; (b) the ratio of land under cereals to total farm land (degree of specialization); (c) the ratio of land under cereals to labor; and (d) the ratio of capital stock to labor. The choice of environmental factors is to a certain extend constrained by data availability. Nevertheless, the farmer's age, the degree of specialization, and technology proxies (such as the ratio of capital to labor and/or the ratio of land to labor) has been considered as relevant environmental variables in almost all earlier empirical studies on the efficiency of crop production (e.g. Latruffe, et al., 2008; Madau, 2007; Tzouvelekas, et al., 2002; Giannakas et al., 2001).

Table 1 presents descriptive statistics for the variables used in the empirical analysis. The sample includes very small as well as very large cereal farms (in terms of land under cereals).

Considerable variability also appears to exist with respect to the use of the production inputs. As far as the environmental variables are concerned, the age of the average farmer is 52, the average degree of specialization is high (above 0.8). The lowest capital to labor ratio is 1.61 and the highest is 313; the lowest land to labor ratio is 0.05 and the highest is 7.54.

Table 1: Descriptive Statistics for the Variables Used in the Empirical Analysis

	Minimum	**Maximum**	**Mean**	**Standard Deviation**
Output (Euros)	700	49136	11441	8298
Labor (hours)	300	7500	1647	1174
Land ($100m^2$)	107	8606	1520	1376
Fertilizers and Pesticides (Euros)	10	30600	4792	4590
Other Costs (Euros)	925	45210	11873	8336
Age of the Owner	31	75	52	10
Degree of Specialization	0.19	1	0.83	0.19
Land to Labor Ratio	0.05	7.54	1.20	1.14
Capital to Labor Ratio	1.61	313.02	66.24	49.94

Starting with the test of global separability, the empirical value of the $\hat{\tau}_n$ statistic is zero and so is the critical value resulted from the bootstrap procedure of Daraio et al. (2010). Global separability, therefore, is consistent with the sample data. This suggests that the environmental factors considered here affect only the distribution of efficiencies and not the attainable input-output combinations (or the shape of the underlying production set).

For the empirical implementation of the unconditional and conditional order-m efficiency estimators one needs to select the size of the partial frontier (m) first. According to De Witte and Kortelainen (2008) the size must be selected in such as way as to leave the percentage of "super-efficient" units more or less stable. Here, the required stability has been achieved for $m = 130$. For the empirical implementation of the conditional order-m estimator, in particular, one also needs to select a kernel function with an appropriate bandwidth. In this study, following Hall et al. (2004) and Li and Racine (2007), we rely on least squares cross-validation for the bandwidth choice (conditional bandwidth estimation) and we use the multivariate product Gaussian kernel.

Table 2 presents the frequency distributions of the estimated unconditional and conditional efficiency scores. The average value of the unconditional scores is 1.16 suggesting that output could be increased by 16 percent, provided that all farms in the sample will follow the same rules of input use as those located on the unconditional partial order-m frontier; 45% of the farms have achieved efficiency scores in the interval [1, 1.25). From these, 58 farms (or 23.3% of the total) are efficient. A considerable proportion of farms (25.3%) have been classified as "super-efficient", while 12.8% appear to be highly inefficient with scores above 1.5. The average value of the conditional efficient estimates is 1.1 suggesting that output could be increased by 10%, provided that farms will follow the same rules of input use as those located on the corresponding conditional partial order-m frontier. The overwhelming majority of farms (80.3%) have achieved efficiency scores between 1 and 1.25. The proportion of "super-efficient" farms has fallen to only 3.2%, the proportion of highly inefficient ones has fallen to 6.4%, while the proportion of efficient has risen to 52.6 %. Overall, accounting for the operational environment leads to a much more concentrated distribution of the estimated efficiency scores suggesting that the operating environment does affect the productive performance of the cereal farms in Greece.

Table 2. Frequency Distribution of the Estimated Unconditional and Conditional Efficiency Scores

	Unconditional Estimates		Conditional Estimates	
Efficiency Score	**No. of Farms**	**% of Farms**	**No. of Farms**	**% of Farms**
[0.85, 1)	63	25.3	8	3.2
[1, 1.25)	116	46.6	200	80.3
[1.25, 1.5)	38	15.3	25	10.1
[1.5, 2.01)	32	12.8	16	6.4

To examine the influence (i.e. favorable or unfavorable) of the environmental variable, we nonparametrically regress the environmental variables on the ratio of the conditional to the unconditional efficiency scores. As in De Witte and Kortelainen (2008) and Jong et al. (2008) the non parametric regression has implemented through the Local Linear estimator (which is less sensitive to boundary effects compared to alternative non parametric estimators such as the Nadaraya- Watson) relying again on least squares cross-validation for the bandwidth choice and on multivariate product Gaussian kernel. Also, for the estimation of each individual effect (through the so-called partial smooth regression plots) the remaining environmental factors have been set at their 50 quantile value (a choice typically made in earlier applications).

Figures 1 to 4 present the partial regression plots.[2] Figure 1 indicates that age has a positive impact on efficiency. This result in line with the findings of Tzouvelekas et al. (2002) and Madau (2007) who assessed the performance of wheat farms in Greece and of cereal farms in Italy, respectively, using stochastic frontier models with inefficiency effects. The experience that comes with age is, ceteris paribus, a proxy for management skills. One, therefore, may conclude that higher management skills work towards a better performance of cereal farms in Greece. Figure 2 indicates that specialization has a positive impact on efficiency. This finding is in agreements with those of Tzouvelekas et al. (2002) and Giannakas et al. (2001) (who also used a stochastic frontier model with inefficiency effects to assess the performance of wheat farms in Canada). The favorable effect of this environmental factor, however, should be evaluated with a proper care. The reason is that although a higher specialization level may increase expected profits, it may also deprive a farm owner of the benefits from diversification; production of agricultural commodities is a risky business and diversification is a reasonable strategy for risk averse agents. The agricultural economics literature offers plenty of empirical evidence that farmers are risk averse and, therefore, they are willing to trade expected profits for lower variability of profits (e.g. Sckokai and Moro, 2006). From Figure 3 the land to labor ratio appears to have a positive effect on the efficiency of cereal farms in Greece. This finding, which provides an indication that cereal farms are overmanned for the area cultivated, appears to be quite reasonable. “Hidden-unemployment” has been a long-lasting problem in Greek agriculture; farm work traditionally has played the role of a substitute for limited employment opportunities in other sectors of the economy. From Figure 4, the capital to labor ratio appears to have a negative effect on efficiency indicating that the farms in the sample are overcapitalized. Since

[2] All computations for the present work have been carried out in *R*. The code utilizes *np* package by Hayfield and Racine (2008).

capital in our work is a stock variable, this result may reflect poor management decisions with regard to purchases of new machinery and equipment and the construction of new building. Our findings vis-à-vis the impact of the two technology proxies on efficiency are in line with those reported in Latruffe et al. (2008) for crop and livestock farms in Poland.

Figure 1. Partial Regression Plot: Impact of Farm Owner's Age

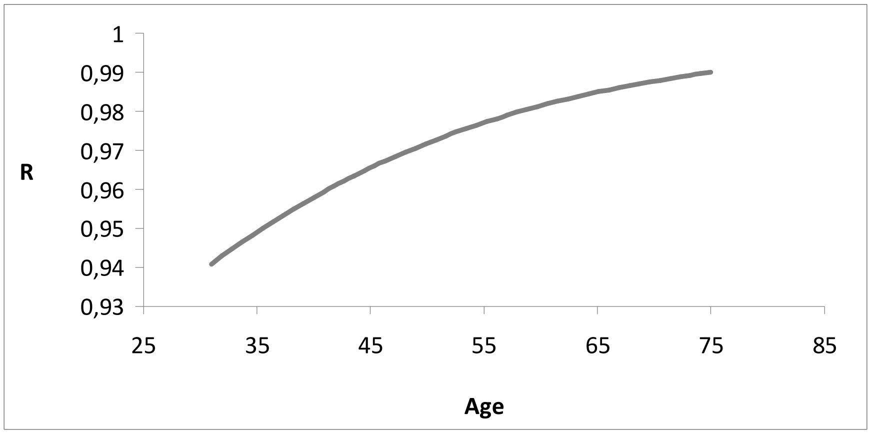


Figure 2. Partial Regression Plot: Impact of Specialization

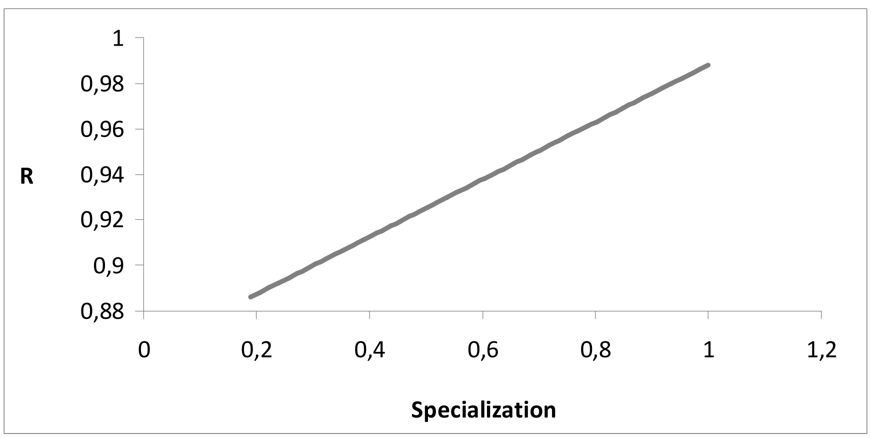


Figure 3. Partial Regression Plot: Impact of the Ratio of Land to Labor

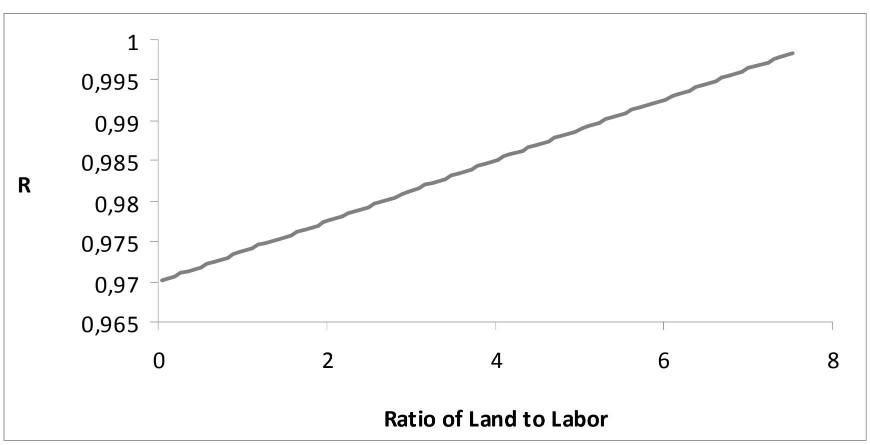
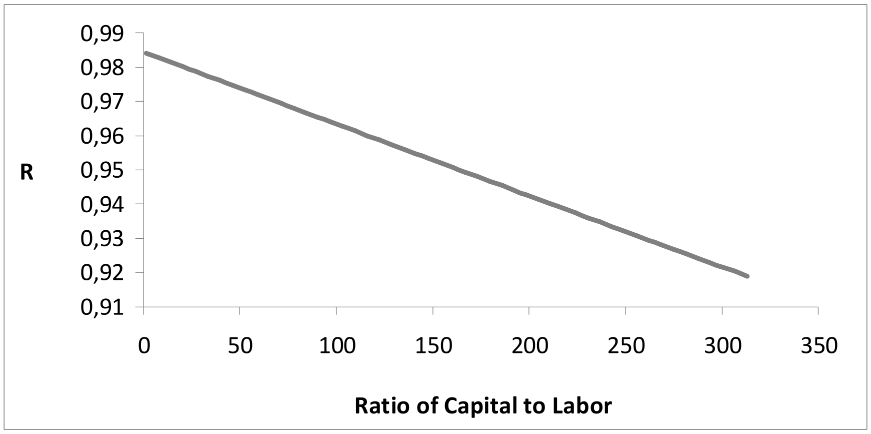


Figure 4. Partial Regression Plot: Impact of the Ratio of Capital to Labor



4. CONCLUSIONS

The measurement and the explanation of efficiency differentials among decision making units has been an important topic of economic research over the last 40 years and it has been pursued using alternative methodologies. This is not accidental, since the efficiency analysis provides valuable information to managers and policy makers regarding the productive performance across a sample of units and the potential for improvements. In this context, the present work investigates the performance of cereal farms in Greece using data from the FADN of the EU and recently developed non parametric robust partial frontier techniques (the order- m estimator). According to our results:

(a) The environmental factors considered (owner's age, degree of specialization and two "technology proxies") affect only the distribution of efficiencies and not the attainable input-output combinations or the shape of the production set.

(b) The unconditional estimates indicate considerable efficiency differentials among the 249 farms in the sample (more than 12 % have been classified an extremely inefficient and more than 25% have been classified as "super-efficient"). The conditional estimates, however, suggest that much of the efficiency differentials disappear once the operational environment is accounted for. Indeed, on the basis of the conditional estimates, almost 80% of the farms achieved efficiency scores below 1.25, while only 3% have been classified as "super-efficient" and 6.5% as extremely inefficient.

(c) The owner's age (a proxy for experience and managerial skills) appears to have a positive impact on the efficiency of the farms in the sample. The same is true for the degree of specialization in the production of cereals and for the land to labor ratio. The capital to labor ratio, however, appeared to have a negative effect on the efficiency. The last two results are probably indications of underutilization of the labor and the capital inputs, respectively, due to the lack of alternative employment opportunities and to poor managerial decisions with respect to machinery and buildings.

ACKNOWLEDGEMENT

De Witte, Kristof is acknowledged for providing the code for the estimations.

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