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BOOTSTRAPPING DECOMPOSED ALLOCATIVE EFFICIENCY WITH FARMER'S ON AND OFF FARM CHOICE[1]

Abstract. *The reliance of farm households on non-farm income is a growing area of research but the relationship between multiple household income sources and the efficient use of family resources has rarely been examined. The main objective of the paper is to contribute to the research stream on the method in Data Envelopment Analysis (DEA) and efficiency measurement. Using 2004 data from Ireland, the paper develops a new framework to decompose allocative efficiency and bootstrap it for all household labour allocations. We also use similar techniques to calculate measures for household technical and scale efficiency. In addition, we bootstrap DEA efficiency measures and regression models simultaneously to remove the effects of dependence among DEA results on the regression estimation. We go on to analyze the determinants of household technical, allocative and scale efficiency.*

Key words: *DEA, Bootstrap, Farm Household Efficiency, Allocative Efficiency, Choice.*

JEL Classification: C61 D13

1. Introduction

The reliance of farm households on non-farm income is a growing phenomenon on Irish farming. From the Agri-vision 2015 report, it was showed that in 2004 about 40% of farm households have some off-farm income and that almost 30% of the farming population are sustainable because of off-farm income (Hennessy, 2004). Internationally the issue of overall household efficiency (as opposed to farm level efficiency) has been studied by Chavas and Aliber (1993) using a stochastic frontier model and by Chavas et al. (2005) using data envelopment analysis (DEA). Within

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Ireland, while work has been carried out on allocation of household labour on and off the farm (Brick et. al., 2005; Keeney, 2000; Hennessy 2004; Eoghan 2006), overall household efficiency has not heretofore been examined. In this paper, following Chavas et al. (2005) we measure overall household efficiency for Irish farms using DEA. We will calculate three measures of efficiency – Technical, Allocative and Scale efficiency. Among them, we concentrate on allocative efficiency which is used to measure farmer’s efficiency in allocating household labour between on-farm work and off-farm job. We also focus on a number of areas omitted by Chavas et al. in their analysis. Specifically, we consider the effects on estimation of the dependency and censoring of the DEA measures, as well as the effects of outliers on the calculation of the measures themselves. Using a smoothed bootstrap technique, based on that of Simar and Wilson (1998), and an econometric regression, we recover DEA standard errors and simultaneously estimate both the specific household efficiency measures and their determinants. In previous work (Zhang and Eoghan, 2007) the authors have considered the link between the original (non-bootstrapped) DEA estimates and stochastic frontier results and found a strong correspondence between the two sets of results for (only) technical efficiency. This paper goes beyond that work in its concern with DEA efficiency sampling properties and estimation issues. We specially focus on the household allocative efficiency only in allocating resources between on and off farm choice while exclude the efficiency in allocating resources on farm work. We go on to discuss the DEA bootstrapping procedures for technical, scale and allocative efficiency. We consider the determinants of efficiency, using simultaneous Tobit estimations, and conclude with a brief discussion of the methods and results.

Consider a farm household with some family members making production and labour allocation decisions. The household uses family labour and all other inputs to produce farm output. In addition, the household members can also spend their time on off-farm activities. Traditionally, the above problems were simplified by measuring farm efficiency using a standard farm-level approach. However, this method needs at least two assumptions: first, the relationship between work time and income must be linear and off-farm income can be interpreted as the wage rate received by the family member from off-farm activities. Second, the farm and off-farm technology is non-joint and the household technology can be expressed completely in terms of the separate technologies as on-farm technology and off-farm technology. So, if the opportunity cost of family labor is not the wage rate and if farm and off-farm activities are part of a joint technology, then measurements produced by the standard farm-level approach would be invalid. In this context, a household efficiency framework would be preferred (Chavas J.P. R. Petrie and M. Roth, 2005). In this paper, following Chavas et. al. (2005) we relax the separability assumptions and prefer the overall household efficiency framework to the farm level one and consider farm households involved in both farm and off-farm activities characterized by use of both on-farm inputs and an off-farm input while producing both on-farm output and off-farm output.

Based on the overall household efficiency framework, we want to measure the farmer's efficiency in allocating household labour on and off the farm, which is the emphasis of our study. However, traditional allocative efficiency measurement only provides the allocative efficiency estimator in allocating all household resources among all production activities. In this paper, we will propose a new method to decompose the whole allocative efficiency in order to obtain the part of whole allocative efficiency for on and off farm choice.

2. Decomposing allocative efficiency

To explain the theoretical underpinning for decomposing allocative efficiency by data aggregation, we apply output oriented technology $\Re$ with $i(i=1,\dots,I)$ observations. Suppose that for each DMU i there is M inputs $\boldsymbol{X}_i=(\boldsymbol{X}_{i1},\dots,\boldsymbol{X}_{iM})\in\Re_+^M$ and J outputs $\boldsymbol{Y}_i=(\boldsymbol{Y}_{i1},\dots,\boldsymbol{Y}_{iJ})\in\Re_+^J$ with corresponding output prices $\boldsymbol{P}_i=(\boldsymbol{P}_{i1},\dots,\boldsymbol{P}_{iJ})\in\Re_{++}^J$. The output oriented technical efficiency DEA with fully disaggregated outputs and inputs can be written as:

$$\theta_i^A(\boldsymbol{X}_i,\boldsymbol{Y}_i)=\max\Big\{\theta \,|\sum_i \lambda_i \boldsymbol{X}_{i,m} \le \boldsymbol{X}_{i,m} \quad m=1,\dots,M; \quad \sum_i \lambda_i \boldsymbol{Y}_{i,j} \ge \theta \boldsymbol{Y}_{i,j} \quad j=1,\dots,J; \quad \sum_i \lambda_i = 1,\ \lambda_i \ge 0 \quad i=1,\dots,I\Big\} \tag{1}$$

$\theta_i^A(\boldsymbol{X}_i,\boldsymbol{Y}_i)$ is pure technical inefficiency. The pure technical efficiency can be computed by $TE_i^A=1/\theta_i^A(\boldsymbol{X}_i,\boldsymbol{Y}_i)$. Technical efficiency estimated by above Equation is variable returns to scale (VRS) efficiency. If we release the constraint of $\sum_i \lambda_i = 1$, the constant returns to scale (CRS) efficiency can be calculated. Then, consider the following linear program to maximize revenue $A(\boldsymbol{X}_i,\boldsymbol{Y}_i)$:

$$A(\boldsymbol{X}_i,\boldsymbol{Y}_i)=\max\Big\{\sum_j \boldsymbol{P}_j \boldsymbol{Y}_j \,|\sum_i \lambda_i \boldsymbol{X}_{i,m} \le \boldsymbol{X}_{i,m} \quad m=1,\dots,M; \quad \sum_i \lambda_i \boldsymbol{Y}_{i,j} \ge \boldsymbol{Y}_j \quad j=1,\dots,J; \quad \sum_i \lambda_i = 1,\ \lambda_i \ge 0 \quad i=1,\dots,I\Big\} \tag{2}$$

Specifically, $EE(\boldsymbol{X}_i,\boldsymbol{Y}_i)=\sum_j \boldsymbol{P}_j \boldsymbol{Y}_{j,i} / A(\boldsymbol{X}_i,\boldsymbol{Y}_i)$ is economic efficiency or aggregate technical and allocative efficiency. Normally, allocative efficiency (AE) is calculated by

$$AE_i(\boldsymbol{X}_i,\boldsymbol{Y}_i)=EE(\boldsymbol{X}_i,\boldsymbol{Y}_i)/TE_i^A(\boldsymbol{X}_i,\boldsymbol{Y}_i), \tag{3}$$

when there is no output aggregation. This allocative efficiency calculated from economic efficiency and pure technical efficiency can be defined as *whole allocative efficiency which measures the efficiency in allocating all resources among all fully* *disaggregated and undividable outputs*. But, if the outputs (or inputs in input oriented DEA) are not fully disaggregated and estimated technical efficiency is biased, then the allocative efficiency calculated by Equation (3) is also biased. We first consider a sub-vector of output which is linearly aggregated with prices as:

$$\boldsymbol{C}_{i,\hat{j}} = \sum_{j=1}^{\hat{j}} \boldsymbol{P}_j \boldsymbol{Y}_{i,j} \qquad i = 1,\dots, I \qquad \hat{j} \le J \tag{4}$$

When some outputs are aggregated using Equation (4), the output oriented technical inefficiency DEA can be expressed as:

$$\theta_{ci}^{B}(\boldsymbol{X}_i, \boldsymbol{C}_{\boldsymbol{i},\hat{\boldsymbol{j}}}, \boldsymbol{Y}_{i,\hat{j}+1},\dots,\boldsymbol{Y}_{i,J}) \tag{5.0}$$

$$= \max \theta \{ | \sum_i \lambda_i \boldsymbol{X}_{i,m} \le \boldsymbol{X}_{i,m} \qquad m = 1,\dots, M; \tag{5.1}$$

$$\sum_i \lambda_i \boldsymbol{Y}_{i,j} \ge \theta \boldsymbol{Y}_{i,j} \qquad j = \hat{j}+1,\dots, J; \tag{5.2}$$

$$\sum_i \lambda_i \boldsymbol{C}_{i,\hat{j}} \le \theta \boldsymbol{C}_{i,\hat{j}} \tag{5.3}$$

$$\sum_i \lambda_i = 1,\ \lambda_i \ge 0 \qquad i = 1,\dots, I \ \} \tag{5.4}$$

and those obtained from the same measure but if all outputs are aggregated into one output variable use Equation(4)

$$\theta_{c}^{C}(\boldsymbol{X}_i, \boldsymbol{C}_{\boldsymbol{i},\hat{\boldsymbol{j}}}) \tag{6.0}$$

$$= \max \theta \{ | \sum_i \lambda_i \boldsymbol{X}_{i,m} \le \boldsymbol{X}_{i,m} \qquad m = 1,\dots, M; \tag{6.1}$$

$$\sum_i \lambda_i \boldsymbol{C}_{i,\hat{j}} \le \theta \boldsymbol{C}_{i,\hat{j}} \tag{6.2}$$

$$\sum_i \lambda_i = 1,\ \lambda_i \ge 0 \qquad i = 1,\dots, I \ \} \tag{6.3}$$

The technical efficiency for aggregated data can be computed by $TE_{ci}^{B} = 1/\theta_{ci}^{B}$ and $TE_{c}^{C} = 1/\theta_{c}^{C}$. According to Fare and Zelenyuk (2002, 2004), it is obvious that θ_{ci}^{B} and θ_{c}^{C} are biased. Therefore, the technical efficiencies computed by them are also downwardly biased because the allocative efficiencies are incorporated in the technical efficiency scores. As showed by Fare and Zelenyuk (2004), the bias bounds of technical efficiency can be given as:

$$TE_{c}^{C}(\boldsymbol{X}_i, \boldsymbol{C}_{\boldsymbol{i}}) \le TE_{ci}^{B}(\boldsymbol{X}_i, \boldsymbol{C}_{\boldsymbol{i},\hat{\boldsymbol{j}}}, \boldsymbol{Y}_{i,\hat{j}+1},\dots,\boldsymbol{Y}_{i,J}) \le TE_{i}^{A}(\boldsymbol{X}_i, \boldsymbol{Y}_i) \tag{7}$$

Because normal allocative efficiency is calculated by dividing economics efficiency by technical efficiency, if economic efficiency is fixed, then we can give:

$$AE_{c}(\boldsymbol{X}_i, \boldsymbol{C}_{\boldsymbol{i}}) \ge AE_{ci}(\boldsymbol{X}_i, \boldsymbol{C}_{\boldsymbol{i},\hat{\boldsymbol{j}}}, \boldsymbol{Y}_{i,\hat{j}+1},\dots,\boldsymbol{Y}_{i,J}) \ge AE_{i}(\boldsymbol{X}_i, \boldsymbol{Y}_i) \tag{8}$$

Banker et al.(2007) propose and proof that the estimated technical efficiency TE_{c}^{C} calculated using Equation (6) is identical to economic efficiency $EE(\boldsymbol{X}_i, \boldsymbol{Y}_i)$ calculated using Equation (2). Then, $AE_c(\boldsymbol{X}_i, \boldsymbol{C_i})$ is equal to 1, because $TE_c^C(\boldsymbol{X}_i, \boldsymbol{C_i}) = EE(\boldsymbol{X}_i, \boldsymbol{C_i})$ when all the outputs are aggregated into one variable. Otherwise, $AE_i(\boldsymbol{X}_i, \boldsymbol{Y}_i)$ is the *whole allocative efficiency* which is calculated from the pure technical efficiency $TE_i(\boldsymbol{X}_i, \boldsymbol{Y}_i)$. According to the above proofed proposition, it is intuitively to know that incorporating the linearly aggregated output using Equation (4) in technical efficiency DEA will incorporate the allocative efficiency (relative to the aggregated outputs) into the technical efficiency. Here, the incorporated allocative efficiency only measures the efficiency in allocating resources among those outputs which are aggregated using Equation (4). In other words, the estimated technical efficiencies using Equation (5) include the allocative efficiencies for the aggregated outputs in Equation (5.3). As a result, the estimated allocative efficiency $AE_{ci}(\boldsymbol{X}_i, \boldsymbol{C}_{\boldsymbol{i},\hat{\boldsymbol{j}}}, \boldsymbol{Y}_{i,\hat{j}+1}, ..., \boldsymbol{Y}_{i,J})$ only measures the efficiency in allocating resources among the outputs in Equation (5.2). Here, it should be noted that AE_{ci} also includes the allocative efficiency for Equation (5.3) as a whole output choice but not the individual outputs aggregated in Equation (5.3). Consequently, the whole allocative efficiency is decomposed into two components. It is also easy to find the individual allocative efficiency $AE_{ic}(\boldsymbol{X}_i, \boldsymbol{C}_{\boldsymbol{i},\hat{\boldsymbol{j}}}, \boldsymbol{Y}_{i,\hat{j}+1}, ..., \boldsymbol{Y}_{i,J})$ for the aggregated outputs in Equation (5.3) by dividing the estimated technical efficiency TE_{ci}^B by pure technical efficiency TE_i^A. The relationship of these allocative efficiency components and technical efficiency can be expressed as:

$$\begin{aligned} AE_i(\boldsymbol{X}_i, \boldsymbol{Y}_i) &= \frac{EE(\boldsymbol{X}_i, \boldsymbol{C_i})}{TE_i^A(\boldsymbol{X}_i, \boldsymbol{Y}_i)} \\ &= \frac{EE(\boldsymbol{X}_i, \boldsymbol{C_i})}{TE_{ci}^B(\boldsymbol{X}_i, \boldsymbol{C}_{\boldsymbol{i},\hat{\boldsymbol{j}}}, \boldsymbol{Y}_{i,\hat{j}+1}, ..., \boldsymbol{Y}_{i,J})} \times \frac{TE_{ci}^B(\boldsymbol{X}_i, \boldsymbol{C}_{\boldsymbol{i},\hat{\boldsymbol{j}}}, \boldsymbol{Y}_{i,\hat{j}+1}, ..., \boldsymbol{Y}_{i,J})}{TE_i^A(\boldsymbol{X}_i, \boldsymbol{Y}_i)} \\ &= AE_{ci}(\boldsymbol{X}_i, \boldsymbol{C}_{\boldsymbol{i},\hat{\boldsymbol{j}}}, \boldsymbol{Y}_{i,\hat{j}+1}, ..., \boldsymbol{Y}_{i,J}) \times AE_{ic}(\boldsymbol{X}_i, \boldsymbol{C}_{\boldsymbol{i},\hat{\boldsymbol{j}}}, \boldsymbol{Y}_{i,\hat{j}+1}, ..., \boldsymbol{Y}_{i,J}) \end{aligned} \tag{9}$$

and: $$AE_{ic}(\boldsymbol{X}_i, \boldsymbol{C}_{\boldsymbol{i},\hat{\boldsymbol{j}}}, \boldsymbol{Y}_{i,\hat{j}+1}, ..., \boldsymbol{Y}_{i,J}) = TE_{ci}^B(\boldsymbol{X}_i, \boldsymbol{C}_{\boldsymbol{i},\hat{\boldsymbol{j}}}, \boldsymbol{Y}_{i,\hat{j}+1}, ..., \boldsymbol{Y}_{i,J}) / TE_i^A(\boldsymbol{X}_i, \boldsymbol{Y}_i) \tag{10}$$

Above functions can be used in the specific application for measuring allocating resources. For example, if we focus on the allocative efficiency component for some specific outputs or inputs which we are interested in, we can aggregate all the other outputs or inputs and then calculate the allocative efficiency component which we want.

3. Measuring allocative efficiency component for on-farm and off-farm choice

Since this study is focused on the effects of off-farm job on the household efficiency, we mainly concern the efficiency in allocating household resources only between on-farm work and off-farm job. As discussed in the earlier section, we can easily decompose the whole allocative efficiency in order to obtain the allocative efficiency component only for on-farm and off-farm choice. In this study, we directly use the data in which the on-farm allocative choice among different agricultural products (such as crop, cattle and sheep) is incorporated into normal technical efficiency measurement by aggregating farm products into one output. In this way, the allocative efficiency computed through dividing economic efficiency by estimated technical efficiency is only the allocative efficiency component for on-farm and off-farm choice. The logic routine for the above method can be explained easily as follows: The individual farmer firstly has to decide whether he will take off-farm job or not and if yes, how much time he will input in the off-farm job. Then, he will allocate the household resources for on-farm inputs for different farm products. This process, in fact, gives two stages in allocating household resources. If we want to know the allocative efficiency in the first stage, the above method can satisfy us. In this paper, the output-oriented household technical efficiency can be defined as:

$$1/TE=\theta\ (x, fl, wl; y, no)=Max(\theta : (x, fl, wl; \theta y, \theta no) \in X, \theta>0) \qquad (11)$$

Here, x refers to on-farm input, fl is on-farm labour time, and wl is off-farm labour time. y is on-farm output and no is off-farm income. In general, the household technical efficiency is >0 and <=1. When TE=1, the household is operated on the production frontier and is technically efficient. It should be noted here that the on-farm output is aggregated output and therefore the technical efficiency estimated from the above Equation will include allocative efficiency component for on-farm investment.

Given household technical efficiency, to calculate household allocative efficiency for on-farm and off-farm choice we need to maximize profit implying the following revenue maximizing problem:

$$R(x, fl, wl; y, no)=Max(y+no : (x, fl, wl; y, no) \in X\ ) \qquad (12)$$

In this function, y is total farm revenue. For the household allocative efficiency component, the AE can be defined as

$$AE(x, fl, wl; y, no)=(y/TE+no/TE)/R \qquad (13)$$

Here, if AE is 1, indicating that the unit farm household is fully efficient in allocating recourses between on-farm and off-farm work. And, if AE is lower than 1, representing that efficiency can be improved by relocating labour time between on-farm and off-farm work. As for scale efficiency, it can be easily computed by dividing CRS technical efficiency by VRS technical efficiency scores. Since aggregated data only influence the estimated technical efficiency and allocative efficiency, scale efficiency will not be affected.

4. The Bootstrap process for DEA and regression

To explain the relationship between the result of Data Envelopment Analysis (DEA) efficiency scores and factors that determine efficiency, some common regression models have been widely used in the literature. However, the problem of the dependent relationship among DEA efficiency scores in the DEA-regression analysis has been widely ignored. Because the DEA efficiency scores are traditionally treated as the response variable in the regression, the basic regression assumption of independence within the sample will be violated, as first recognized by Mei and Patrick (1999). To overcome the problem of the inherent dependence among the DEA efficiency scores they use a procedure involving bootstrapping the DEA model and regression analysis simultaneously. However, the method proposed by Mei and Patrick only considers the Ordinary Least Square regression as the second-stage analysis and, furthermore, applies a common bootstrap procedure which is currently considered as a having some weaknesses, as described in Simar and Wilson (1998). Due to the nature of efficiency scores ranging from 0 to 1, the Tobit regression model is almost certainly a better regression method than OLS. In addition, the smoothed bootstrap procedure for DEA, first proposed by Simar and Wilson (1998), is currently treated as a preferred method to bootstrap DEA. This paper will use the smoothed bootstrap procedure to bootstrap DEA and Tobit regression simultaneously and applies this method to not only technical efficiency but also to allocative and scale efficiencies. Simar and Wilson (2007) propose that the Tobit model using maximum likelihood (ML) will yield biased bootstrap estimators. The reason is that they use the ML estimators to smooth the original data. Thus, the ML Tobit or truncated regression estimators will influence bootstrapped efficiency estimators directly. Because ML estimators of censored or truncated model are sensitive to strict assumptions (such as homoscedasticity, normality …), Using the ML estimators of censored or truncated model are not the appropriate method in smoothing original data for bootstrap. In this study, to circumvent above problems, we still apply the standard smoothing process proposed by Simar and Wilson (1998). In addition, Tobit ML regression is applied only in the second stage regression, which will not influence the smoothing process and therefore the bootstrapped DEA efficiency[2]. The smoothed bootstrap procedure assumes that, if the known data generating process (DGP) can consistently estimate the unknown data, the known bootstrap distribution can mimic the original unknown distribution. By this assumption, the bootstrap process will generate scores that can mimic the distributions of the unobserved DGP. (Simar and Wilson 1998, 2000(a), 2000(b)). Considering the nature of DEA estimations, the smoothed bootstrap procedure is based on the DEA estimators themselves by drawing with replacement from the original estimates of efficiency score. The steps of smoothed bootstrap procedure for bootstrapping both technical efficiency scores and Tobit regression are:

[2] In fact, there are at least three econometric methods to regress the estimated results from DEA. We choose Tobit regression in this paper as it is widely used.

1. Assuming there are n observations in original sample, solve the original DEA model and obtain the reciprocal $\hat{\theta}$ of technical efficiency.

2. Estimate the regression model $1/\hat{\theta}_i = f(\beta_k, V_{ki}) + \varepsilon_i$ by Ordinary Least Square (OLS), here i denotes the observations from 1 to N, V_k denotes explanatory variables (k=1,…,K), and β is the vector of coefficients; regard the OLS coefficient value as the initial value for Tobit Log Likelihood function censored at both '0' and '1'; maximize the Tobit Log Likelihood function to provide original β coefficients of regression model.

3. Draw a random sample $\hat{\theta}^*$ with replacement from the original estimated sample $\hat{\theta}$.
4. Smooth the sampled values using the following functions:

$$\begin{aligned}\tilde{\theta}_i^* &= \hat{\theta}_i^* + h\varepsilon_i^* (if \hat{\theta}_i^* + h\varepsilon_i^* \le 1), or \\ \tilde{\theta}_i^* &= 2 - \hat{\theta}_i^* - h\varepsilon_i^* (if \hat{\theta}_i^* + h\varepsilon_i^* > 1).\end{aligned} \tag{14}$$

Here, h is a smoothing parameter, and ε is a randomly drawn error term. 'h' can be obtained by the "normal reference rule", which calculates h by following function:

$$h = \left(\frac{4}{p+q+2}\right)^{1/(p+q+4)} \times N^{\frac{-1}{p+q+4}} \tag{15}$$

where p is the number of inputs, q equals the number of outputs and N is the number of observations in the sample. Furthermore, according to Desli et. al.(2004), we can also choose the value of the window width that minimizes the approximate mean integrated square error as follows: $h = 0.9AN^{-1/5}$, where $A = min$ (standard deviation of $\hat{\theta}$, inter-quartile range of $\hat{\theta}/1.34$). The minimum value of 'h' from the above two methods is used as the smoothing parameter.

5. Calculate the value θ^* by adjusting the smoothed sample value using the following function:

$$\theta_i^* = \bar{\beta}^* + \frac{1}{\sqrt{1 + h^2 / \hat{\sigma}_{\hat{\theta}}^2}} (\tilde{\theta}_i^* - \bar{\beta}^*), \tag{16}$$

$$where: \bar{\beta}^* = \sum_{i=1}^{n} \hat{\theta}_i^* \Big/ n, \quad and \quad \hat{\sigma}_{\hat{\theta}}^2 = \frac{\sum_{i=1}^{n} (\hat{\theta}_i - \bar{\hat{\theta}})^2}{N}$$

Here, $\hat{\sigma}_{\hat{\theta}}^2$ is the sample variance of original estimated efficiency scores, and $\bar{\hat{\theta}}$ is the sample mean of them.

6. Obtain the new outputs by adjusting the original outputs using the ratio $\hat{\theta}_i / \theta_i^*$

7. Solve the DEA model again using the adjusted outputs to obtain final bootstrapped $\dddot{\theta}_i$ as the reciprocal of efficiency scores.

8. If there are some infeasible observations in final DEA results, restart this procedure from step 4 again to make sure that there is no invalid and infeasible bootstrapped DEA results.
9. For each bootstrap sample S, estimate the regression model using each bootstrapped DEA result as the response variable by OLS and Tobit methods to yield S sets of coefficients.
10. Repeat steps 3-9 S times to provide S sets of valid estimates. Although this procedure will only provide S sets of valid estimated scores, the real bootstrap times is far higher than that due to some infeasible bootstrap results (The procedure may restart from step 4 again at step 8).

This smoothed bootstrap procedure is a little different from that of Simar and Wilson 1998, 2000(a), 2000(b) in that our step 8 is used to drop infeasible results that emerge in bootstrapping process. In this analysis, S is denoted as 1000, and therefore 1000 valid samples will be generated for each observation.

After the desired samples are generated, the bias of the original estimate of $\hat{\theta}$ can be calculated as follows:

$$Bias\hat{\theta}_i = E_s(\dddot{\theta}_i) - \hat{\theta}_i$$
$$where E_s(\dddot{\theta}_i) = \sum_{s=1}^{S} \dddot{\theta}_{si} \Big/ S \tag{17}$$

Therefore, the bias-corrected estimator of θ can be expressed as:

$$\tilde{\theta}_i = \hat{\theta}_i - Bias\hat{\theta}_i \tag{18}$$

Here, $\tilde{\theta}_i$ is the final bias-corrected theta which can be directly used to calculate bias-corrected technical efficiency estimators.

The standard error (SE) of theta estimators can be calculated by:

$$SE_i = \sqrt{\frac{\sum_{s=1}^{S} (\dddot{\theta}_{si} - E_s(\dddot{\theta}_i))^2}{S-1}} \tag{19}$$

To estimate confidence intervals for the θ, the unknown distribution of $\hat{\theta}_i - \theta_i$ can also be approximated by the known distribution of $\dddot{\theta}_i - \hat{\theta}_i$. Then,

$\Pr ob(-b_\alpha \le \hat{\theta}_i - \theta_i \le -a_\alpha) = 1-\alpha$ can be mimicked by

$\Pr ob(-b^*{}_\alpha \le \dddot{\theta}_i - \hat{\theta}_i \le -a^*{}_\alpha) = 1-\alpha^*$ conditioned on the original data. According to Simar and Wilson (1999), the algebraic value of $\dddot{\theta}_i - \hat{\theta}_i$ should first be sorted, then deleting (α/2)*100% of the elements at either end of this sorted array, and finally letting $-b^*_\alpha$ and $-a^*_\alpha$ equal to the endpoints of the sorted array. In this paper, we choose the confidence interval from 5% to 95%.

As a result, it is obtained that:

$$\Pr ob(-b^*{}_\alpha \leq \ddot{\theta}_i - \hat{\theta}_i \leq -a^*{}_\alpha) \approx 1-\alpha \tag{20}$$

Finally, the 1- α confident interval of Theta can be approximated as:

$$\hat{\theta}_i + a^*_\alpha \leq \theta_i \leq \hat{\theta}_i + b^*_\alpha \tag{21}$$

As for the regression model, the standard error, $se_k(\hat{\beta}_{si})$, will be estimated by the sample standard deviation of the bootstrap replications of $\hat{\beta}_{ski}$. The standard error of β coefficients can be expressed as:

$$se_k(\hat{\beta}_{si}) = \sqrt{\sum_{s=1}^{S} (\hat{\beta}_{si} - \overline{\beta}_i)^2 \Big/ (K-1)} \tag{22}$$

where

$$\overline{\beta}_i = \frac{\sum_{s=1}^{S} \hat{\beta}_{si}}{S}$$

Here, there are ‘kth’ $se_k(\hat{\beta}_{si})$ representing the standard errors for ‘K’ explanatory variables. ‘*i*’ still indicates observations, and S is the number of bootstrap times. Based on the bootstrap standard errors, a t-test will be used to test the hypothesis of Tobit coefficients

It should be noted here that for the DEA model the (θ) is bootstrapped, and therefore the standard error and confidence interval was estimated for θ. But, the response variable of the regression model is technical efficiency which also equals to the reciprocal of theta.

With regard to scale efficiency, the scale efficiency score can be directly calculated through dividing CRS-TE (constant return to scale technical efficiency) by VRS-TE (variable return to scale technical efficiency).

Based on the available VRS-TE bootstrap method, we just need to solve an additional CRS-TE DEA in step 7, and in step 8 we should ensure that there is no infeasible result in both the VRE-TE result and CRS-TE result. Furthermore, for scale efficiency, the OLS and Tobit regression should regress on scale efficiency scores. In addition, because the scale efficiency is estimated through dividing CRS TE by VRS TE, we bootstrap the scale efficiency score directly instead of its reciprocal.

However, for allocative efficiency (AE), because it is calculated from dividing economic efficiency (EE) by technical efficiency, the bootstrap procedure needs to be displayed in detail.

1. Solve several original DEA models to obtain the heta of economic efficiency $\hat{\theta}_{EE}$, and theta of allocative efficiency $\hat{\theta}_{AE}$ (the VRS-TE scores can use the estimated original technical efficiency scores in the first procedure directly). Here, $\hat{\theta}_{EE}$ and $\hat{\theta}_{AE}$ also are the reciprocals of EE and AE.

2. Estimate the regression model $1/\hat{\theta}_{AE\,i} = f(\beta_{AEk}, V_{AEki}) + \varepsilon_i$ by OLS and Tobit, again *i* denotes the observations from 1 to N, V_k denotes explanatory variables (k=1,…,K), and β is coefficients, but they are all based on allocative efficiency.

3. Draw a random sample $\hat{\theta}_{EE}{}^*$ with replacement from the original estimated sample $\hat{\theta}_{EE}$.

4. Smooth the sampled values from $\hat{\theta}_{EE}{}^*$ using the same method as in the TE procedure step 4.

5. Calculate the value $\theta_{EE}{}^*$ by adjusting the smoothed sample value using the same function in the TE procedure step 5.

6. Obtain the new outputs by adjusting the original outputs using the ratio $\hat{\theta}_{EEi} / \theta^*_{EEi}$.

7. Solve several DEA models using the adjusted outputs to obtain final bootstrapped Theta of economic efficiency $\dddot{\theta}_{EEi}$, Theta of new technical efficiency $\dddot{\theta}_{TEi}$, and finally calculate allocative efficiency and its reciprocal (Theta) through dividing $\dddot{\theta}_{EEi}$ by $\dddot{\theta}_{TEi}$.

8. If there are some infeasible observations in DEA results for economic efficiency and new technical efficiency, restart this procedure from step 4 again until there is no infeasible bootstrapped DEA results for both EE and new TE.

9. For each bootstrap sample S, estimate the regression model for allocative efficiency by OLS and Tobit methods to yield S sets of coefficients.

10. Repeat steps 3-9 S times to provide S sets of valid estimates.

This procedure is different from the first procedure for technical efficiency in that it uses the Theta of economic efficiency to adjust original outputs and therefore yields not only economic efficiency but also the new technical efficiency for each bootstrap. This not only provides the sensitivity analysis of DEA results but also gives appropriate standard errors of DEA results, even though the efficiency scores computed from the DEA are dependent.

5. Data and variables

All the data comes from the Irish National Farm Survey managed by Teagasc (The Irish Agriculture and Food Development Authority). It is cross-sectional data for 2004. The number of observations of farms with on and off-farm labour for 2004 is 606 farms. The farm output chosen is total farm output. In addition, the subsidies which are directly related to the production will also be included in the total farm output (Cattle and dairy subsidies, sheep subsidies, and crop subsidies). The off-farm output is off-farm income. The farm input includes farm utilized land, labour input, total direct costs. The off-farm input is only off-farm work time. Table 1 depicts the descriptive statistics of the farm and off-farm variables. On-farm labor input is measured in standard man days. Costs and farm output are measured in euro. The other output variable, off-farm work income, ranges from 1 to 16. Here, off-farm income was measured by ordered code in the farm survey. 1 indicated the income range from 0 to €4000, two represented the income range from €4000 to €8000, and so on. We combined the income code of householder and that of spouse together. Farm land is measured in hectares. The variables used in the Tobit estimation of the determinants of technical, allocative and scale efficiency are described in the next section.

Table 1. Descriptive statistics of farm variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Labor days	606	277.8883	233.8486	4.49	1370.5
Farmland	606	48.42373	38.83952	4.09	371.1
Total costs	606	23860.41	26694.39	689	230092.9
Off-farm work hours	606	1740.647	939.3244	25	4368
Off-farm work income	606	6.529703	3.423537	1	16
Farm output	606	72971.87	75882.25	3951	590424

Table 2. Descriptive Statistics of original and bootstrapped efficiency scores

	No. of Obs.	Minimum	Maximum	Mean	Std. Deviation
Original technical efficiency	606	0.199	1	0.733	0.171
Average for bootstrapped technical efficiency	606	0.59	1	0.691	0.085
Bias-corrected technical efficiency	606	0.116	1	0.764	0.238
Original allocative efficiency	606	0.243	1	0.88	0.175
Average for bootstrapped allocative efficiency	606	0.631	1	0.974	0.051
Bias-corrected allocative efficiency	606	0.144	1	0.83	0.226
Original scale efficiency	606	0.446	1	0.941	0.097
Average for bootstrapped scale efficiency	606	0.317	0.999	0.931	0.087
Bias-corrected scale efficiency	606	0.371	1	0.94	0.119

6. Results for bootstrap DEA

Table2 depicts the summary statistics of calculated efficiencies. The original technical efficiency[3] values range from 0.2 to 1 with a mean of 0.733; the average technical efficiency for 1000 bootstrap samples ranges from 0.596 to 1 with a mean of 0.691, while the bias-corrected technical efficiency has the widest range, ranging from 0.116 to 1 with a mean of 0.764. The original allocative efficiency ranges from 0.243 to 1 with a mean at 0.88; the average allocative efficiency changes from 0.63 to 1 with a mean at 0.97; and the bias-corrected allocative efficiency ranges from 0.144 to 1 with a mean at 0.83. The original scale efficiency ranges from 0.441 to 1 with a mean at 0.94; the average scale efficiency ranges from 0.317 to 0.999 with a mean at 0.93, and the bias-corrected scale efficiency ranges from 0.371 to 1 with a mean at 0.94.

Table 3. The frequency distribution of technical efficiency, allocative efficiency, and scale efficiency

	Original TE		Bias-corrected TE		Original AE		Bias-corrected AE		Original SE		Bias-corrected SE	
	Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent
0.1-0.2	1.00	0.17	4.00	0.66			7.00	1.16				
0.2-0.3	2.00	0.33	19.00	3.14	6.00	0.99	22.00	3.63				
0.3-0.4	9.00	1.49	32.00	5.28	11.00	1.82	23.00	3.80			2.00	0.33
0.4-0.5	44.00	7.26	47.00	7.76	23.00	3.80	26.00	4.29	3.00	0.50	9.00	1.49
0.5-0.6	85.00	14.03	71.00	11.72	21.00	3.47	28.00	4.62	9.00	1.49	11.00	1.82
0.6-0.7	120.00	19.80	68.00	11.22	31.00	5.12	31.00	5.12	12.00	1.98	19.00	3.14
0.7-0.8	133.00	21.95	53.00	8.75	41.00	6.77	35.00	5.78	32.00	5.28	26.00	4.29
0.8-0.9	87.00	14.36	49.00	8.09	64.00	10.56	81.00	13.37	54.00	8.91	43.00	7.10
0.9-1.0)	56.00	9.24	45.00	7.43	360.00	59.41	201.00	33.17	461.00	76.07	218.00	35.97
1.0	69.00	11.39	218.00	35.97	49.00	8.09	152.00	25.08	35.00	5.78	278.00	45.87
Total	606.00	100.00	606.00	100.00	606.00	100.00	606.00	100.00	606.00	100.00	606.00	100.00

Table3 depicts the frequency distribution of the estimated original and bias-corrected efficiency scores for 606 Irish farm families. As for the original TE, besides 69 fully technically efficient farm households whose TEs are 1, the calculated technical efficiencies concentrate on the range from 0.6 to 0.8, in which there are 253 households occupying about 42% of total farm households. The number of farm households with '1' bias-corrected TE scores are high, up to 218 and occupying 36% of all observations. For some families the differences in the original technical

[3] Please note, all the technical efficiency estimators include allocative efficiency component for on-farm allocation; All the allocative efficiency estimators are only allocative efficiency component for allocating household labour between on and off farm.

efficiency might come from the random error which can not be fully captured by DEA framework. The estimated scores of bias-corrected allocative efficiencies, ranging from 0.1 to 1.0, are spread more widely than those of original allocative efficiency ranging from 0.2 to 1.0. As for the bias-corrected allocative efficiency scores, the number of farm families located in the range from 0.9 to 1.0 is reduced to 201, far lower than the number of farm families (360 households) in the same range for the original allocative efficiency. Meanwhile, compared with the original allocative efficiency scores, the numbers of observations in the range from 0.8 to 0.9 (81 households) and the fully efficient observations (152 households) have increased. In Table3, the frequency distribution of the original scale efficiency is also listed. The bias-corrected scale efficiency scores are spread more evenly than the original ones. The number of farm families located in the range from 0.9 to 1.0 is 218 which is less than the half of the number of farm families (461 households) in the same range for the original scale efficiency. On the other hand, the numbers of fully efficient farm households is high up to 278. Again, this is likely due to the random error which is taken into account by bootstrapped results but ignored by the original DEA model. The frequency table overall shows the greater range of the bias corrected measures; but also shows a greater frequency of “1” values for bias-corrected technical and allocative efficiency, compared to the original values, and fewer values between .9 and 1. A change of this nature is to be expected if, indeed, the effect of outliers on original efficiency measures is reduced by bootstrapping. Figures 1-3 below go on to show the relationship between the three bias-corrected efficiency measures and 3 of the key household inputs – on-farm labour, farm size and off-farm labour.

Figure 1: Bias-corrected Efficiency and On-farm Labor Days (Lowess Curve)

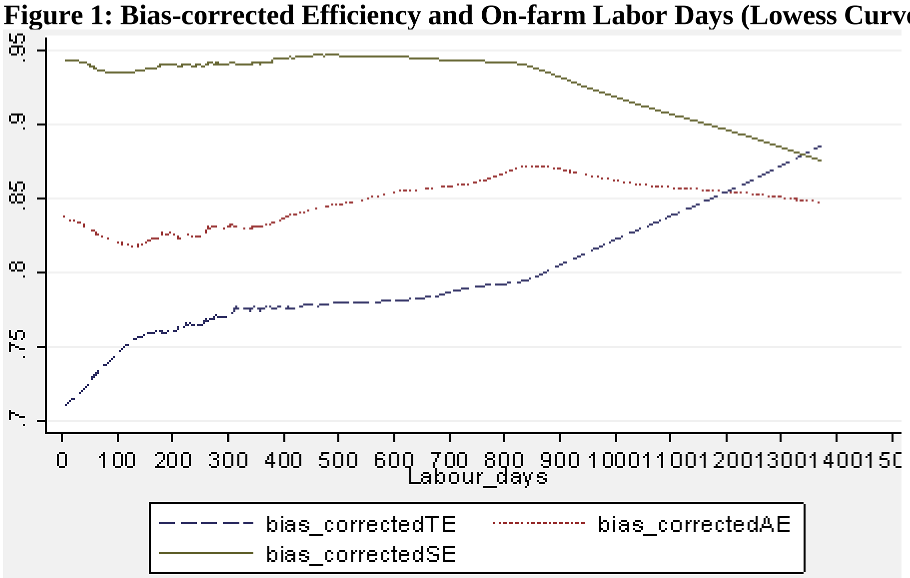

Figure 2: Bias-corrected Efficiency and Farm Size (Lowess Curve)

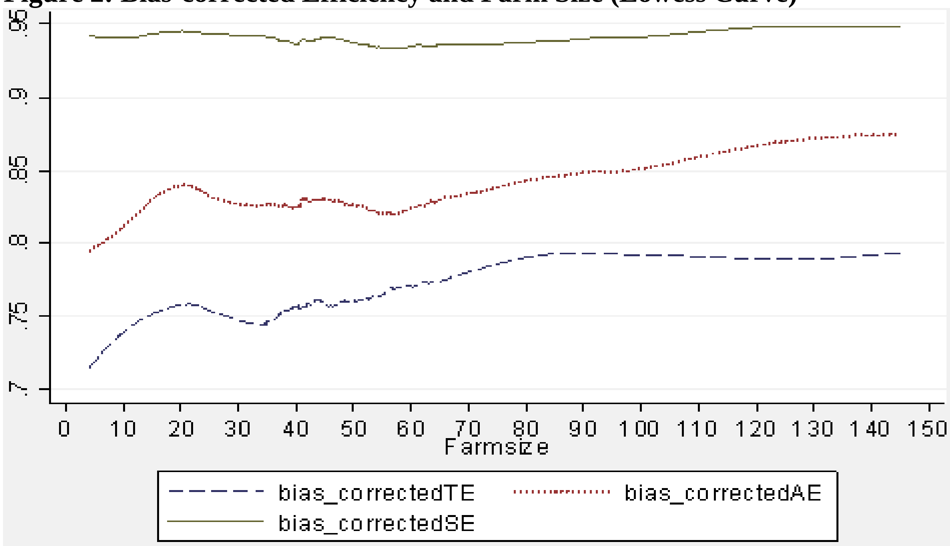

Figure 3: Bias-corrected Efficiency and Off-farm Work Hours (Lowess Curve)

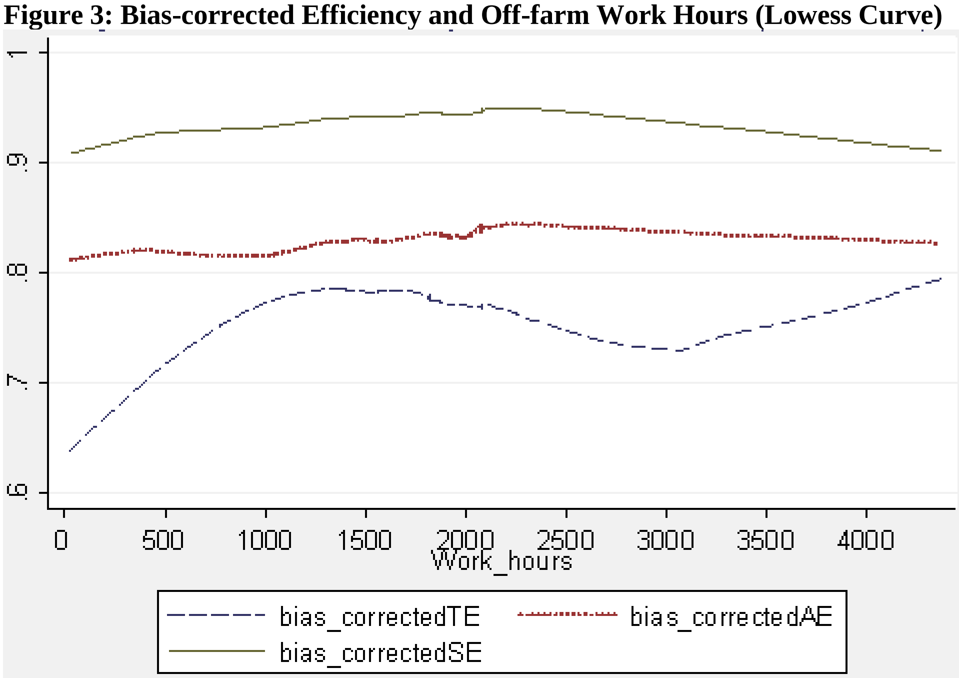

Figure 1 depicts the Lowess curve for bias-corrected efficiencies and on-farm labour. Bias-corrected technical efficiency increases with the increase of on-farm labour inputs in any range. But, in the range from 100 to about 900 labour days, it increases very slowly. Allocative efficiency, on the other hand, decreases in the range from 0 to 100 on-farm labour days; after that it increases in the range from 100 to 900 labour days, and finally decreases again. There are about 438 farm families (occupying 72% of total farm families) located in the range in which the bias-corrected allocative efficiency is increasing with on-farm days. For very high numbers of on-farm days (above 900), scale efficiency falls. There are only 16 farm families in this range.

Figure 2 depicts the Lowess curve for bias-corrected efficiencies and farm size. For farms from 0 to about 20 hectares, the bias-corrected technical and allocative efficiency show a large increase (about 101 farm families are located in this range occupying about 15% of all farm households). However, from 20 to about 34 hectares, the bias-corrected technical and allocative efficiencies decrease (there are 144 farm families occupying 24% of total households in this range.). And then, both efficiencies tend to rise. This is an important result, suggesting households in very small or very large farms are likely to be more efficient, overall, than households on the medium sized (model) Irish farm. The bias-corrected scale efficiency does not change clearly with the increase in farm size in any range.

Figure 3 depicts the Lowess curve for bias-corrected efficiencies and off-farm working hours. Bias-corrected scale and allocative efficiencies do not change clearly with the increase in off-farm working hours. However, the bias-corrected technical efficiency changes greatly with the increase of off-farm work hours. From 0 to about 1200 annual off-farm work hours (up to about one fairly active part-time off-farm job), the bias-corrected technical efficiency has a large increase (about 200 farm families are located in this range occupying about 33% of all farm households). However, from 1200 to about 3000 off-farm work hours (from between one part-time and close to two full-time jobs), the bias-corrected technical efficiency decreases sharply (there are 337 farm families occupying 56% of total households in this range.). The bias-corrected technical efficiency increases again with the increase of off-farm work hours beyond the three thousand mark (both partners working full-time off-farm). This “cubic” nature of this result echoes the previous result for farm size.

7. Regression variables and results

Considering the latent factors influencing inefficiency, the censored Tobit model is used with 1 as an upper bound and is estimated simultaneously with the efficiency measures. As opposed to the variables used in measuring efficiency, the explanatory variables here (in table 4 below) reflect idiosyncratic factors that may influence the performance of farm households and therefore the efficiency scores.

Table 4 . The descriptive statistics of variables for Tobit models

Types	Variables	Mean	*St. Dev.*
Subsidies and Pensions	Subsidies for land not in use (€)	17.61	30.30
	Environmental subsidies (€) (including disadvantage area payment, rural environmental protection scheme, and environmentally sensitive area grants)	42.15	39.21
	Householder pension (=1 if householder has pension)	0.04	0.24
	Pension of others (the number of other house members who have pension)	0.23	0.57
General	Long term loan (Amounts) (€)	82.58	370.80
	Medium term loan (Amounts) (€)	87.19	233.26
	Insurance (€)	9.61	12.97
	Full time on farm (the number of house members working on farm full-time excluding householder and spouse)	0.05	0.22
	Part time on farm (the number of house members working on farm part-time excluding householder and spouse)	0.16	0.44
	Soil code (the soil code for soil quality, lower number represents better soil quality)	2.90	1.39
	Land rented (acs.)	0.27	0.55
	Consultant fees (Fees spent on consultants) (€)	7.03	6.66
	Teagasc fees (Fees spent on Teagasc advices) (Teagasc is the Irish national body providing integrated research, advisory and training services to agriculture and the food industry.) (€)	1.82	2.71
Marriage status	Married (=1 if householder is married)	0.86	0.35
	Separated (=1 if householder is separated)	0.01	0.09
	Widow (=1 if householder is widowed)	0.02	0.13
Demographic data	Gender (=1 if householder is male)	0.97	0.16
	Householder age	47.65	9.62
	Number of House members	4.16	1.67
	Pre-school (the number of house members in the age of pre-school)	0.24	0.56
	Primary-edu (the number of house members receiving primary education)	0.57	0.93
	Second-edu (the number of house members receiving second-level education)	0.50	0.79
	Third-edu (the number of house members receiving third-level education)	0.30	0.60
Farm types	Farm-specialist dairy	0.27	0.44
	Farm- mixed dairy	0.10	0.31
	Farm- cattle rearing	0.26	0.44
	Farm- sheep	0.11	0.32
	Farm- tillage	0.08	0.28

Table 5.1. Bootstrap Tobit results

variables	Technical efficiency Original Coef.	Technical efficiency Mean of bootstrap Coef.	Allocative efficiency Original Coef.	Allocative efficiency Mean of bootstrap Coef.	Scale efficiency Original Coef.	Scale efficiency Mean of bootstrap Coef.
Constant	0.67090***	0.7109***	0.7972***	0.9616***	0.9232***	0.9772***
Subsidies for land not in use	0.00097***	-0.00003	0.0012***	0.00021**	0.00045**	0.00019
Environmental subsides	-0.00035	-0.00032	-0.0003***	0.00008	-0.0002**	-0.00008
Householder pension	0.09713***	0.05844*	0.0436***	0.00223	-0.00034	-0.0021
Pension of other	-0.01139	0.00281	0.0144***	0.00279	0.0138***	0.00914**
Long term loan	0.00001	0.00002	-0.00001**	-0.00001	0.00000	0.00000
Medium term loan	0.00007*	0.00004	0.00001	-0.00001	0.00001	-0.00001
Insurance	0.00140	0.00029	0.0014***	0.00015	0.00071	0.00033
Full time	0.01698	0.01165	0.00759	-0.00392	0.00928	0.00599
Part time	-0.01842	-0.01581	0.0134***	0.00525*	0.00450	0.00797
Soil code	-0.00815	0.00166	-0.019***	-0.0042**	-0.00333*	-0.00059
Land rented	0.03179*	0.02079	0.0256***	0.00501	0.01812**	0.00340
Consult fees	0.00209	0.00017	0.0020***	0.00054**	0.00046	0.00009
Teagasc fees	0.00289	-0.00053	0.0016***	-0.00003	0.0029***	0.0034***
Married	0.01925	-0.02178	-0.0621***	-0.00333	-0.01761	0.00201
Separated	0.05180	0.01000	0.1379***	0.0351***	0.00788	-0.02075
Widow	-0.00023	0.02309	0.0639***	0.01991**	0.01880	0.01032
Male Gender	-0.00747	0.00039	0.0373***	0.00440	-0.00938	-0.02469*
Householder age	0.00043	0.00216**	0.0024***	0.00034*	0.0011***	-0.00023
No. house members	0.01243	-0.00332	-0.00244	0.00027	-0.007**	-0.00518*
Pre-school	0.00061	0.00451	-0.00804**	-0.00099	0.00111	-0.00139
Primary-edu	-0.00198	0.00507	0.0102***	0.00202	0.00661**	0.00533
Second-edu	-0.01184	0.00083	-0.0210***	-0.0061**	0.00285	0.00109
Third-edu	-0.00240	0.00439	0.00701**	-0.00235	0.0148***	0.0126***
Farm-specialist dairy	-0.01673	-0.07753**	0.1058***	0.01354	0.0393***	0.01827
Farm- mixed dairy	-0.07967**	-0.0757**	0.01981**	-0.00077	0.01647	0.00706
Farm- cattle rearing	-0.06322**	-0.03390	-0.0698***	-0.01198*	-0.028***	-0.0228**
Farm- sheep	-0.01149	-0.04441	-0.0387***	-0.00791	-0.0255**	-0.0259**
Farm- tillage	0.02097	-0.06554*	0.00923	0.00119	-0.00592	-0.02535*

Note: * significant at 10% level, ** significant at 5% level, *** significant at 1% level. S.E. in this table is the standard error over bootstrap samples.

Table 5.2 S.E. of Bootstrapping Tobit results

variables	**Technical efficiency**	**Allocative efficiency**	**Scale efficiency**
Constant	0.08010	0.01898	0.02395
Subsidies for land not in use	0.00032	0.00008	0.00022
Environmental subsides	0.00024	0.00008	0.00010
Householder pension	0.03400	0.00535	0.01108
Pension of other	0.01574	0.00289	0.00416
Long term loan	0.00002	0.00000	0.00001
Medium term loan	0.00004	0.00001	0.00001
Insurance	0.00093	0.00011	0.00052
Full time	0.03365	0.00729	0.00976
Part time	0.01755	0.00295	0.00512
Soil code	0.00585	0.00189	0.00205
Land rented	0.01712	0.00367	0.00921
Consult fees	0.00157	0.00027	0.00090
Teagasc fees	0.00283	0.00054	0.00088
Married	0.02946	0.00740	0.01238
Separated	0.07781	0.01297	0.03686
Widow	0.06538	0.00933	0.01516
Male Gender	0.04853	0.00977	0.01257
Householder age	0.00100	0.00020	0.00039
No. house members	0.00946	0.00176	0.0028
Pre-school	0.01584	0.00318	0.00383
Primary-edu	0.01197	0.00219	0.00323
Second-edu	0.01253	0.00303	0.00364
Third-edu	0.01589	0.00323	0.00427
Farm-specialist dairy	0.03634	0.01020	0.01342
Farm- mixed dairy	0.03372	0.00852	0.01190
Farm- cattle rearing	0.02563	0.00675	0.00881
Farm- sheep	0.02955	0.00665	0.01061
Farm- tillage	0.03520	0.00688	0.01293

In arriving at table 5 (including table 5.1 and 5.2), we follow the procedure recommended by Mei Xue and Harker (1999), who recommend reporting, for efficiency reasons, the mean of the bootstrap coefficients and the use of only the standard errors calculated from the bootstrap. They also recommend including the original coefficient for comparison purposes. We do this, but hardly comment further on the original coefficients except to say that there are a good deal fewer significant variables when the mean bootstrapped coefficients are used and that the majority of the results with the original coefficients also seem quite plausible. Looking at the coefficients for technical efficiency, and controlling always for farm type, only the pension and age variables are significant, suggesting technical efficiency increases with householder's age. With regard to allocative efficiency, age is again significantly positive, indicating elder farmers probably have higher efficiency in allocating their labour between on and off farm. Having children at secondary school is – as might be expected – negative. Paying a farming or financial consultant, having better soil and having more non-production related subsidies are all positive. The first and last of these are as expected, but the positive soil quality result was expected rather for the technical efficiency results. Finally, the more other family members there are (apart from the main couple) helping part-time on the farm, then – as might be expected – allocative efficiency is also higher.

With regard to scale efficiency, having a female household head improves it (there are very few female household heads). Scale efficiency is also associated with smaller households, with those with children in third level education, with those taking Teagasc advice and with those where some household member (not the head) has pension money coming in. From these results, there are certainly points worth making: age is associated with greater efficiency, "unearned" money coming into the house (pensions or non-production related subsidies) is also associated with greater efficiency. Seeking consultants' or an extension service's advice also seems to be associated with improved efficiency.

8. Conclusion

One of main contributions of this paper is the development of a framework for decomposing allocative efficiency according to our study preference. In addition, the method for bootstrapping efficiency and Tobit regressions simultaneously is proposed, based on adjustments to existing techniques. We outline the procedure to smoothly bootstrap technical efficiency and Tobit regression, and then extend it to scale efficiency and, specifically, to allocative efficiency. Using these techniques, overall household level efficiency including both on-farm and off-farm work is estimated. From the estimated results of technical efficiency (VRS), Irish farm families appear to have great potential to increase their household revenue through improving technical efficiency on both farm work and off-farm work. From the estimated allocative efficiency components, Irish farm households also have some room to improve their allocation of household labour inputs in both farm work and off-farm work. Scale efficiency also has some small potential to be increased.

From the Lowess curve for bias-corrected efficiencies an interesting issue comes from a clear cubic curve relationship between off-farm work hours and the bias-corrected technical efficiency. From 0 to about 1200 off-farm work hours, the bias-corrected technical efficiency increases with the increase of off-farm work hours. However, from 1200 to about 3000 off-farm work hours, the bias-corrected technical efficiency decreases. And then, the bias-corrected technical efficiency increases again with the increase of off-farm work hours. Thus, those doing very little or a lot off the farm seem to have improved household efficiency while doing a moderate amount off the farm (roughly equivalent to one full-time or two part-time jobs off-farm) seem to have reduced it. A similar, though less striking, relationship exists between farm size and technical efficiency. As for the bias-corrected allocative efficiency, there seems to be a clear relationship with farm size (again, cubic) and on-farm labour days (generally positive, though declining at first).

In going on to look at the determinants of variations in different kinds of household efficiency, we have had some, albeit limited, success. The variable "rented land" is an interesting case. It is shown to have significant effects on all original efficiencies but in no case is it significant for the mean bootstrapped results. The lack of significance in the bootstrapped case is due either to the removal of dependence in the dependent variable, or to the removal of outliers, or both, occasioned by the bootstrapping procedure. More positively, consultants have significant and positive effects on allocative efficiency components. Teagasc advices impact scale efficiency. Some other variables, such as having other family members working on the farm or having children in secondary school, have clear effects on allocative efficiency measuring only on and off farm choice. Age improves both technical efficiency and allocative efficiency component. Obviously, further research and comparisons are needed to improve the reliability and quality of these results, but this paper takes a first step in decomposing allocative efficiency and using DEA to analyze farm household efficiency in Ireland in a way that attempts to overcome most of the perceived weaknesses of DEA as a tool to accomplish this task. The research is new also in its emphasis on the household, not only the farm. The separability assumptions needed to separate on and off-farm efficiency analysis (primarily - linearity of off-farm returns; non-jointness of production) are quite strong and the investigation of the applicability of these assumptions is an area worth concentrating on in the immediate future.

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