# Chapter 1
# Efficiency Measures in the Agricultural Sector: The Beginning

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**Abstract** The agricultural productivity is often based on non-parametric models (DEA), or stochastic models (SFA). In this initial article, the editors start by pointing that the models (DEA and SFA) allow estimating the efficiency of the production frontier and their structural forms. Then, it is presented, in general terms, the differences between DEA and SFA models: DEA model involves the use of technical linear programming to construct a non-parametric piecewise surface, and SFA models comprise econometric models with a random variable, or an error term, including two components: one to account for random effects and another to take care of the technical inefficiency effects. Finally, it shows a comparison between the two approaches (SFA and DEA) and the advantages and disadvantages of their utilizations.

**Keywords** Data Envelopment Analysis • Models • Non-parametric • Parametric • Stochastic Frontier Analysis

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## 1.1 Introduction

The agricultural policy analysis, mainly, the agricultural productivity, is often based on support models like mathematical programming (non-parametric, non-stochastic) models or econometric (stochastic, parametric) models. These models are very useful for decision support because they give an orientation of what are the main characteristics of agricultural farms and how it is possible to solve some of the problems found.

The deterministic production frontier is an approach where all observations are in one side of the frontier and all deviations from the frontier are attributed to inefficiency. On the other hand, in the stochastic approach, all observations are on both sides of the frontier, and it is possible to separate between random errors and differences in inefficiency.

The most popular approaches to calculate efficiency are: (1) the non-parametric techniques (Charnes et al. 1978), the Data Envelopment Analysis (DEA) based on the linear programming tools; and (2) parametric techniques (Aigner et al. 1977; Meeusen and van den Broeck 1997), the Stochastic Frontier Analysis (SFA) – stochastic frontier production (SFP) – based on econometric tools.

## 1.2 The Data Envelopment Analysis: DEA

The use of optimization tools to calculate efficiency with Data Envelopment Analysis (DEA) was developed by Charnes et al. (1978) from earlier work by Farrell (1957). This method has been used to estimate the efficiency in the organizational units in several areas (Cooper 1999).

DEA is a non-parametric method to estimate efficiency, involves the use of technical linear programming to construct a non-parametric piecewise surface (or frontier) over data, for it to be able to calculate efficiency relative to his surface (Coelli 1996a). Any farm that lies below the frontier is considered to be inefficient. DEA permits to construct a best-practice benchmark from the data on inputs and outputs (Jaforullah and Whiteman 1999). In opposite, parametric techniques, as econometric methods, construct a stochastic frontier.

DEA involves the concept of efficiency, and Farrell (1957) had decomposed the efficiency into (1) technical efficiency and (2) allocative efficiency. The technical efficiency measures the maximum equiproportional reduction in all inputs, which still allows continued production of given outputs. The allocative efficiency reflects the ability of a firm to use the inputs in optimal proportions, given their respective prices. These two concepts form the concept of economics efficiency (Coelli 1995). The allocative inefficiency measures the magnitude of consequent loss. Similar considerations are applied to economics efficiency and inefficiency.

Therefore, the overall measure of technical efficiency can be disaggregated into three components: (1) pure technical efficiency due to producing within an isoquant frontier, (2) congestion due to overutilization of inputs and (3) scale efficiency due to deviations from constant returns to scale (Weersink et al. 1990).

Technical efficiency under constant returns to scale is estimated by relating each observation to the frontier under constant returns to scale (CRS). Technical efficiency under variable returns to scale (TEVRS) and technical efficiency under constant returns to scale (TECRS) are equal for farms that operate in the region of constant returns to scale, i.e. these farms have a scale efficiency of one. As a consequence, these farms have a scale efficiency (SCAL) of one (Lansink and Reinhard 2004).

One of the most popular computer programs used to solve DEA problems is the Data Envelopment Analysis Computer Program (DEAP) developed by Coelli (1996b). This program is based on the optimization model used by Charnes et al. (1978), but considering the input components $v_{ik}x_{ik}$ and a scaling constant $l$ (normally 100%):

$$\text{Max}: \; Ef_a = \sum_{r=1}^{s} \mu_{ra} y_{ra}$$

$$\text{s.t.}: \sum_{i=1}^{m} v_{ia} x_{ia} = l$$

$$\sum_{r=1}^{s} \mu_{rk} y_{rk} \le \sum_{i=1}^{m} v_{ik} x_{ik} \quad k = 1, \ldots, n$$

$$\mu_{rk}, v_{ik} \ge 0 \quad i = 1, \ldots, m \quad r = 1, \ldots, s \tag{1.1}$$

$y_{rk}$ is the level of output $r$ used by decision-making unit $k$, $x_{ik}$ is the level of input $i$ used by decision-making unit $k$ and $\mu_{rk}$ and $v_{ik}$ are the non-negative variable weights associated to the solution of decision-making unit $k$, of output ($r$) and inputs ($i$), respectively; $s$ is the number of outputs considered and $m$ the number of inputs considered.

The DEA approach has been applied to the agricultural field to estimate the efficiency by different researchers in different parts of the world, such as Arzubi and Berbel (2002), Reinhard and Thijssen (2000), Reinhard et al. (2000), Jaforullah and Whiteman (1999), Fraser and Cordina (1999), Gonzalez et al. (1996), Färe and Whittaker (1995) and Weersink et al. (1990).

## 1.3 Stochastic Frontier Analysis (SFA) or Production (SFP)

The Stochastic Frontier Analysis (SFA) is a parametric approach which was originally and independently proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977) as pointed out by Battese and Coelli (1988). The SFA involves an unobservable random variable associated with the technical inefficiency in production of individual firms. In addition to the random error in a traditional regression model (Battese and Broca 1997), the SFA considers that an error term has two components: one to account for random effects and another to account for the technical inefficiency effects (Coelli 1995).

The most common different functional forms for stochastic frontier are the tanslogarithmic and the Cobb-Douglas production functions.

One of the most common software to solve parametric problems is FRONTIER version 4.1, developed by Coelli (1996b), often selected to estimate the models.

The efficiency model (*model I*) is proposed by Battese and Coelli (1995), and the $v_{it}$ is the technical inefficiency variable which is defined by

$$v_{it} = \{\exp\left[-\eta\left(t - T\right)\right]\} v_i, \quad \text{with} \quad i = 1, \ldots, N, \quad \text{and} \quad t = 1, \ldots, T \tag{1.2}$$

where $\eta$ is an unknown parameter to be estimated; and $v_i$ with $i = 1, 2, \ldots, n$, are independent and identically distributed non-negative random variables, which are assumed to account for technical inefficiency in production and obtained by truncations (at zero) of the normal distribution, with unknown mean and unknown variance, $\sigma^2$.

This model specifies that the technical inefficiency effects for the sample in the earlier periods of the panel are a deterministic exponential function of the inefficiency effects for the corresponding firms in the last years of the panel (i.e. $v_{it} = v_i$, given the data for the *i-th* firm is available in the period, $T$).

Given the Eq. (1.2), the expectation of the mean technical efficiency is

$$\mathrm{TE} = \exp\left(-v_i\right), \tag{1.3}$$

and it is estimated considering the technical inefficiency effects ($v_i$).

The *model I* only permits to determine the technical efficiency, but to know more about inefficiency, Battese and Coelli (1995) presented the *model II* (inefficiency model) which permits to incorporate in *model I* the variable that could cause inefficiency in the firms. In this model, the technical inefficiency effects are defined by

$$u_{it} = z_{it}\delta + w_{it}, \quad \text{with} \quad i = 1, \ldots, N, \quad \text{and} \quad t = 1, \ldots, T \tag{1.4}$$

where $z_{it}$ is a $(1 \times M)$ vector of explanatory variables associated with technical inefficiency effects; $\delta$ is a $(M \times 1)$ vector of unknown parameters to be estimated; and $w_{it}$ are the unobservable random errors which are assumed to be independently distributed and obtained by truncation of a normal distribution with unknown mean and variance, $\sigma^2$, such that $u_{it}$ is non-negative ($w_{it} \geq -z_{it}\delta$).

This approach is widely used by many authors such as Pascoe et al. (2001), Torres et al. (2002), Munzir and Heidhues (2002), Reinhard et al. (1999), Reinhard et al.(2000), Alvarez and Gonzalez (1999), Webster et al. (1998), Franco (2001), Daryanto et al. (2002), Lawson et al.(2004), Battese and Coelli (1988), Battese and Broca (1997), Battese and Coelli (1992), Brummer (2001), Hallam and Machado (1996) and Venâncio and Silva (2004).

## 1.4 DEA and SFA Approaches: A Comparison

DEA is very useful to calculate efficiency (Lansink and Reinhard 2004) and provides a simple way to calculate the efficiency gap that separates each producer's behaviour from the best practice, which can be assessed from actual observations of the inputs and outputs of efficient firms (Reig-Martínez and Picazo-Tadeo 2004).

The DEA model allows the comparison of a firm to a benchmark (set of best producers), and then the measure of efficiency is relative to the best producer in that group of firms; it is not necessarily the maximum real output per input used.

Sharma et al. (1999) argue that the main advantage of DEA is the fact that avoids the parametric specification of technology such as the assumptions for the distribution of the inefficiency term.

The DEA approach has the advantage of considering many inputs and many outputs simultaneously. This has as a consequence the increasing of efficiency with the number of variables: more variables, higher efficiency (Reig-Martínez and Picazo-Tadeo 2004; Silva et al. 2004). DEA does not require a parametric specification of a functional form to construct the frontier (Silva et al. 2004), and it was considered by Coelli and Perelman (1999) as the main advantage of DEA; it is very easy to perform because it does not require a priori knowledge on the functional form of the frontier and benchmarking (best-practice reference) to real firms (Lauwers and van Huylenbroecks 2003). DEA does not impose any assumptions about functional form; hence, it is less prone to misspecification and does not take into account the random error and consequently is not subject to the problems of assuming an underlying distribution about error term (Pascoe and Mardle 2000). To these authors, DEA does not take account of statistical noise, and the efficiency estimates may be biased if the production process is largely characterized by stochastic elements.

The mathematical programming models are non-stochastic, and so they cannot have the values, of inefficiency and noise, separately. It is a non-parametric technique and not as effective as SFA, as a specification error (Reig-Martínez and Picazo-Tadeo 2004). The major limitations of DEA is that it is difficult, conceptually, to separate the effects of uncontrollable environmental variables and measurements error, from the effect of differences in farm management and the presence of outliers (Silva et al. 2004).

The DEA model is deterministic and attributes all the deviations from the frontier to inefficiencies; a frontier estimated by DEA is likely to be sensitive to measurement errors or other noise in data (Sharma et al. 1999) and may attribute stochastic noise to the inefficiency scores and thus may be more sensitive to outliers (Lauwers and van Huylenbroecks 2003).

DEA has more flexibility in that they avoid a parametric specification of technology and assumptions about the distribution of efficiency, whilst allowing curvature conditions to be imposed easily (Lansink and Reinhard 2004).

The main DEA disadvantage to Coelli and Perelman (1999) is that when the calculation of shadow prices are desired, only a range of prices can be derived for the efficient firms. The production surface constructed by DEA is a series of intersecting planes. The efficient frontier points that define this frontier surface (primarily) lie at the intersections of these planes. Hence, when one attempts to measure shadow prices for these efficient points, only a range of price ratios can be observed (corresponding to the slopes of the planes involved).

A disadvantage of the DEA approach is that there are no single objective criteria (it is different from a CRS to a VRS) against assessment of the model, and the models only provide a reasonable representation of the actual frontier (or set of frontiers) (Pascoe and Mardle 2000).

The econometric approach is stochastic, and then it allows distinguishing the two effects: statistical noise from productive inefficiency. It is also parametric and can mix the effect of misspecification of functional form (can be flexible) with inefficiency. The flexible functional form could imply the multicollinearity, and some theoretical conditions could be violated (Reinhard et al. 2000)

One of the most important characteristics of econometric models (SFA) is that it allows a specification in the case of panel data and the construction of confidence intervals (Reinhard et al. 2000).

The SFA models only have in this functional form one output and various inputs. SFA allows a correction for stochastic events, but assumes a parametric specification for the production technology, which can confuse efficiency results. SFA calculated by a translog specification, the curvature conditions (concavity inputs) are not globally satisfied, SFA makes an explicit assumption about the distribution of the inefficiency term (Lansink and Reinhard 2004).

Stochastic estimations incorporate a measure of random error but impose an explicit functional form and distribution assumption of data (Pascoe and Mardle 2000). SFP approach produces a set of statistics against which the models can be judged in terms of goodness of fit and alternative methods can be discriminated against.

One advantage of parametric methods is that they permit the testing of hypotheses such as those relating to the significance of included inputs and/or outputs, returns to scale and so on (Coelli and Perelman 1999).

The advantage of DEA over SFA is that the technological frontier is constructed without imposing a parametric functional form for inefficiency or on a deviation from it (Reig-Martínez and Picazo-Tadeo 2004).

Sharma et al. (1999) found that DEA is more sensitive to outliers and other noise in the data, but DEA results are more robust than those obtained from the parametric approach.

The most important point of frontier approach is that it deals with stochastic noise and allows statistical test of hypotheses pertaining to production structure and the degree of inefficiency. The imposed structural form and the explicit distributional assumption for the inefficiency term are the worst point of parametric techniques (Sharma et al. 1999).

There are several differences between these two kinds of tools. One of the differences pointed by Reinhard et al. (2000) was about the construction of a production frontier and the calculation of efficiency relative to the frontier.

Coelli and Perelman (1999) point as advantages of parametric and non-parametric approaches the influence of outliers, although the stochastic frontier method attempts to account this problem, the translog distance function estimates obtained by this tool, has not been very successful.

In some situations in DEA, when there are non-stochastic elements affecting a firm's level of production, the greater DEA flexibility allows a better representation in the level of the distribution of technical efficiency (Pascoe and Mardle 2003). In this case, the imposition of a single production frontier (SFA model) may result that some inefficient firms probably are efficient.

Paul et al. (2004) compare the stochastic and determinist methods and conclude that in terms of level, the SFP (Stochastic Frontier Production) measures suggest more scale economies and technical efficiency, and DEA measures more "technical progress" or shifts out of the technological frontier over time.

In the construction of confidence intervals, Brummer (2001) points that intervals for SFA are wider than DEA, because the assumptions of DEA are more restrictive (deterministic structure). The SFP model estimated a higher mean technical efficiency compared with DEA models (Pascoe and Mardle 2000).

Reinhard et al. (2000) compared the SFA and DEA approaches and concluded that both methods can estimate efficiency scores, but only SFA incorporates noise. DEA is a deterministic model and could not identify the environmental detrimental variables in the model.

In summary, the main difference between SFA and DEA is about the way the production possibility is estimated; that means, DEA does not require a functional form and SFA does. The DEA (deterministic) approach ignores the random effects (noise), but SFA approach takes it into account; then in the DEA model, any deviation is considered inefficiency but in SFA is considered noise and inefficiency. Both approaches give the same indication of the characteristics that affect efficiency, and the outliers can affect the scores of efficiency. Although the scores of inefficiency are similar, usually the value of the DEA approach is lower than the one obtained by SFA. The SFA approach allows distinguishing the inefficiency from the error term: it is identified what is due to inefficiency and what is due to random disturbances such as measurement of error, luck, bad weather, pest or diseases.

Both approaches seem useful, and their use will depend on the objectives of the analysis.

## 1.5 Why This Book?

The aim of this book is to aggregate several articles on efficiency measures and techniques for the agricultural sector.

Increasing efficiency in the agricultural sector and in rural communities can improve the financial situation of farms and communities, given the continuous pressure on margins of agricultural products. This fact has been highly recognized and studied by researchers since many years. But, in the current context of economic crises in Europe, these themes are, more than ever, especially pertinent as several southern countries need to increase exportation and decrease importation.

This book starts by describing techniques like Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) and proceeds by presenting several applications exploring the particularities of the agriculture sector as the abundance of subsidies, strong competition between regions worldwide and the need for efficient production systems. The introductory chapters make possible for the nonexpert reader to understand the book, and clear applications lead the reader to practical problems and solutions.

Applications include the estimation of technical efficiency in agricultural grazing systems (dairy, beef and mixed) and specifically for dairy farms. The conclusions indicate that it is now necessary to help small dairy farms in order to make them more efficient. These results can be compared with the technical efficiency of a sample of Spanish dairy processing firms presented by Magdalena Kapelko and co-authors.

In the work by Silva and Venâncio, SFA is used for the estimation of inefficiency models. Another approach involved the assessing of the importance of subsidies in farms efficiency as they are so relevant for farmers. Another application studies the level of technical efficiency in the Andalusia oil industry implementing environmental and non-discretionary variables.

There are also articles on applying DEA techniques to agriculture using R software and making it more user friendly. The "Productivity Analysis with R" (PAR) framework establishes a user-friendly data envelopment analysis environment with special emphasis on variable selection, aggregation and summarization.

The editors have confidence that this book is useful and informative for students and researchers. Feel free to send feedback to amendes@uac.pt.

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