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ON MEASURES OF THE AGRICULTURAL EFFICIENCY – A REVIEW

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ABSTRACT*. *The paper aims to discuss the theoretical preliminaries of the efficiency measurement (benchmarking) and presenting a survey on manifestations of suchlike analyses in the agricultural economics. The definitions of efficiency and measures thereof are presented and followed by description of the mathematical models for efficiency measurement. The paper particularly focuses on data envelopment analysis and stochastic frontier analysis which are the two celebrated methods for analysis of the productive efficiency. The scientometric analysis was carried out in order to fathom the current trends of frontier benchmarking in agriculture. The literature survey on the latter issue is also presented. The Lithuanian agricultural sector still facing the consequences of post-communist transformations should be analysed by the means of frontier measures to a higher extent. The discussed methods and research frameworks would certainly increase the effectiveness of the strategic management decisions.

KEYWORDS: efficiency, agriculture, frontier techniques, data envelopment analysis, stochastic frontier analysis.

JEL classification: C14, C40, Q10.

Introduction

Performance management aims at identifying and spreading the best practices within an organization, sector, or the whole economy. The relative performance evaluation – benchmarking – is the systematic comparison of one production entity (decision making unit) against other entities (Bogetoft, Otto, 2011). Indeed, benchmarking is an important issue for both private and public decision makers to ensure the sustainable change. Due to Jack, Boone (2009), benchmarking invokes several positive outcomes: indeed, the results of benchmarking might encourage changes within an organisation; in addition, the ultimate goal of changes (i.e. vision) would be clearer; the evidence-based support for changes can be facilitated; the model organizations can be identified; some reference points can be established to monitor the progress.

Within any economic sector, appropriate strategic decisions should stem from an integrated analysis of the multi-faceted environment. In particular, the agricultural sector rewards even more attention as it receives a vast amount of public funds and, on the other hand, is subject to numerous regulations. It is the benchmarking that is of crucial importance for decision making regarding sustainable agricultural development. A prospective outcome of proper decisions made is increase in the productive efficiency, gains of which render lower costs along with higher profits as regards the producer and more favourable prices as regards the participants of the agricultural supply chain (Samarajeewa *et al.*, 2012). Nauges *et al.* (2011) presented the following factors stressing the need for research into agricultural efficiency. First, agricultural producers (i.e. farmers) usually are owners of certain land areas and these the place they live on, therefore the ordinary assumption that only efficient producers are to maintain their market activity usually does not hold in agriculture; moreover, suchlike adjustments would result in various social problems. Second, it is policy interventions – education, training, and extension programmes – that should increase the efficiency. Third, policy issues relating to farm structure are of high importance across many regions.

In order to perform appropriate benchmarking it is necessary to fathom the terms of effectiveness, efficiency, and productivity. One can evaluate effectiveness when certain utility or objective function is defined (Bogetoft, Otto, 2011). In the real life, however, decision-makers are usually not able to establish reasonable utility functions and these are only revealed implicitly via an instance of empirical analysis (e.g. benchmarking). Finally, productivity means the ability to convert inputs to outputs. There can be a distinction made between total factor productivity (Solow, 1957) and partial (single factor) productivity. The productivity growth is a source of a non-inflatory growth and thus should be encouraged by a means of benchmarking and efficiency management.

As it was already noted by Alvarez, Arias (2004), Gorton, Davidova (2004), the frontier techniques can be considered as the primal methods for analysis of efficiency and productivity in agriculture as well as in other sectors. Indeed, the frontier methods can be grouped into parametric and non-parametric ones. In addition, further distinctions can be made.

Lithuanian farming system is still underperforming if compared to the western standards. Thus, it is important to identify certain types of farming which are the forerunners or laggards in terms of operation efficiency. Furthermore, both public and private investments are needed in the agricultural sector to improve its efficiency and productivity (OECD, FAO, 2011). The appropriate allocation of such investments, however, requires a decision support system based on multi–objective optimization. Consequently, it is important to develop benchmarking frameworks and integrate them into the processes of the strategic management. The forthcoming programming period of 2014–2020 together with the new Rural Development Programme will certainly require suchlike management decisions. Up to now, only a handful of studies attempted to analyse the farming efficiency in Lithuania (see, e.g., Rimkuvienė *et al.*, 2010). Moreover, these papers were focused on diachronic analysis or different farming types were analysed by employing single–period data.

The paper is therefore organized as follows. Section 1 presents the definitions of efficiency and describes measures thereof. The following Section 2 overviews the mathematical models for efficiency measurement, namely data envelopment analysis and stochastic frontier analysis. Finally, Section 3 presents results of the scientometric analysis and a literature review on frontier benchmarking in agriculture.

1. Definitions and Measures of Efficiency

Understanding the concept of efficiency is a key prerequisite for a sound productivity and efficiency analysis. Indeed, we can simply define productivity as a ratio of an (aggregate) output over an (aggregate) input. The relative efficiency then measures the distance between a given amount of inputs (outputs) and the highest attainable amount of inputs (outputs); cf. Daraio, Simar (2007). In principle, this equals to comparison of the observed and "ideal" productivity.

It was Koopmans (1951) who coined the term efficiency in the sense that we are now concerning about. Indeed, Koopmans defined an efficient decision making unit (DMU) as follows: *A DMU is fully efficient if and only if it is not possible to improve any input or output without worsening some other input or output*. Obviously, the latter definition resembles Pareto efficiency. Accordingly, the former definition is referred to as Pareto–Koopmans Efficiency. Note that even it enabled to identify efficient and inefficient DMUs, it did not allow for quantification of the degree of inefficiency.

Therefore, Debreu (1951) analysed the problem of resource utilization thus offering a measure of the productive efficiency, which is known as coefficient of resource utilization. The measure introduced by Debreu is a radial measure of technical efficiency. This type of measures defines a maximal possible equiproportionate contraction in all the variable inputs (in case of input-oriented analysis), which implies that the ratios among input quantities remain stable (Daraio, Simar, 2007; Fried *et al.*, 2008).

The two aforementioned concepts were summarised by Farrell (1957), who, along the lines of Debreu (1951), Koopmans (1951), defined a framework for frontier-based analysis of efficiency as well as described the two kinds of *economic efficiency*, viz. *technical efficiency* and *allocative efficiency* (note that some different terms were used initially). It is worth to note, that Farrell (1957) focused on agricultural efficiency in the United States. One can treat technical efficiency as an extent and ability to maintain the maximum possible output conditioned on a certain combination of inputs and technology, similarly the allocative efficiency measures the ability of a certain DMU to adjust the input use given respective marginal costs (Kalirajan, Shand, 2002). Indeed, it is due to Farrell (1957) that information about input prices is not always available or reliable. Accordingly, technical efficiency is treated as a preferred measure of the productive efficiency.

The two more types of efficiency can be found in economic literature. These are scale and structural efficiency. Scale efficiency captures the loss in productivity due to prevailing returns to scale (i.e. scale of operation). Indeed, certain restrictions on the underlying returns to scale can be imposed. For instance, Farrell (1957), Charnes *et al*. (1978) assumed constant returns to scale (CRS) which means that no decrease in productivity (i.e. overall efficiency) is allowed due to scale inefficiency. Later on, Banker *et al.* (1984) introduced restriction implying variable returns to scale (VRS), which subsequently enabled to estimate scale efficiency as a ratio of the overall technical efficiency (CRS score) over the pure technical efficiency (VRS score). As regards the structural efficiency, it can be defined as an industry-level feature describing performance of a certain sector, which is dependent on both sector's structure and performance of its firms. For instance, one sector can be considered as a more efficient one if its firms operate relatively closer to the production frontier as opposed to other sectors. Practically, this can be checked by establishing hypothetic representative firms for each sector of interest (e.g. mean values) and comparing the associated efficiency scores, yet other schemes are also possible.

Production technology can be described in terms of the Debreu–Farrell measures following the definition of efficiency given by Koopmans definition. In the sequel we will introduce the key notation and definitions related to analysis of efficiency (Fried *et al.*, 2008). Say DMUs (producers, public entities, other objects of interest) transform the sets of inputs $x = (x_1, x_2, ..., x_m) \in \Re_+^m$ into the corresponding sets of outputs $y = (y_1, y_2, ..., y_n) \in \Re_+^n$. The sets of inputs and outputs define the production set (production possibility set):

$$T = \{(x, y) | x \text{ can produce } y\}. \quad (1)$$

At this point, we can define Koopmans efficiency as the limiting amount of inputs and outputs. Indeed, a certain production plan $(x, y) \in T$ is Koopmans-efficient if, and only if, $(x', y') \notin T$ for $(-x', y') \geq (-x, y)$.

It often desirable to define a technology set in terms of either inputs or outputs (Kumbhakar, 2012). In these circumstances, input requirement and output correspondence sets are utilised:

$$I(y) = \{x | (x, y) \in T\}, \quad (2)$$

$$O(x) = \{y | (x, y) \in T\}. \quad (3)$$

For efficiency analysis, it is often more important to estimate the minimal values of inputs given a certain level of outputs. The quantities of interest are referred to as the isoquants or boundaries of the production set *T* defined in the input space. Using the radial terms (Farrell, 1957), for all $y \in \Re_+^n$ there is an associated input isoquant:

$$isoI(y) = \{x | x \in I(y), \lambda x \notin I(y), \lambda < 1\}. \quad (4)$$

Analogously, the maximal output given a certain level of inputs $x \in \Re_+^m$ is represented by a transformation curve:

$$isoO(x) = \{y | y \in O(x), \lambda x \notin O(x), \lambda > 1\}. \quad (5)$$

Even though a certain production plan is located on the efficient frontier as defined in Eqs. 4–5, it must not necessarily be efficient in terms of Pareto-Koopmans definition. The latter situation occurs whenever a production plan is weakly efficient under assumption of free disposability. Indeed, this implies the presence of input or output slacks. The strong efficiency is maintained in certain subsets of the boundaries *I*(*y*) and *O*(*x*):

$$effI(y) = \{x | x \in I(y), x' \notin I(y), \forall x' \leq x, x' \neq x\}, \quad (6)$$

$$effO(x) = \{y | y \in O(x), y' \notin O(x), \forall y' \geq y, y' \neq y\}. \quad (7)$$

Observe that $effI(y) \subseteq isoI(y) \subseteq I(y)$ and $effO(x) \subseteq isoO(x) \subseteq O(x)$.

Efficiency is quantified by considering a distance between an observation and its projection onto the boundary of a production set (production frontier or surface in the primal approach). For this purpose, the distance functions are applied. The simplest forms of the distance functions are Shepard distance function, and Farrell efficiency measure. Shepard (1953) defined the input distance function as the maximal possible contraction of inputs:

$$D_I(x, y) = \max\{\lambda | (x/\lambda, y) \in I(y)\}. \quad (8)$$

Here $D_I(x, y) \geq 1$ for all $x \in I(y)$, and $D_I(x, y) = 1$ for $x \in isoI(y)$. Reciprocally, the Farrell input-oriented measure of efficiency is the minimal input contraction:

$$TE_I(x, y) = \min\{\theta | (\theta x, y) \in I(y)\}. \quad (9)$$

with $TE_I(x, y) \leq 1$ for $x \in I(y)$, and $TE_I(x, y) = 1$ for $x \in isoI(y)$.

Comparing Eqs. 8 and 9 we arrive at the following relation:

$$TE_I(x, y) = 1/D_I(x, y). \quad (10)$$

Distance to the production frontier can also be measured in terms of output change. Accordingly, the output-oriented Shepard and Farrell measures are given as:

$$D_O(x, y) = \min\{\lambda | (x, y/\lambda) \in O(x)\}, \quad (11)$$

$$TE_O(x, y) = \max\{\phi | (x, \phi y) \in O(x)\}, \quad (12)$$

$$TE_O(x, y) = 1/D_O(x, y), \quad (13)$$

where $TE_O(x, y) \geq 1$ for $y \in O(x)$, and $TE_O(x, y) = 1$ for $y \in isoO(x)$.

In an input-output space, the input- and output-oriented measures define movement towards different directions (cf. *Figure 1*). Indeed, the observed input-output bundle (x_0, y_0) can move in the direction of the production frontier spanning *T* by (i) contracting inputs and hence arriving at an efficient point $(\theta x_0, y_0)$ or (ii) expanding outputs and hence arriving at an efficient point $(x_0, \phi y_0)$.

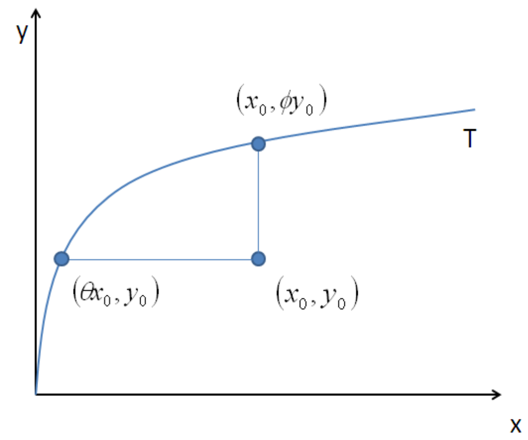

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Figure 1. **Technical Efficiency Measurement in Terms of Farrell Measures**

As it was already said, non-directional efficiency measures maintain a radial movement and thus constant structure of the input-mix. Yet certain situations require to consider a directional (non-radial) movement towards the production frontier. Non-radial movement can be facilitated by altering inputs and outputs simultaneously or altering only certain inputs or outputs (sub-vector distance).

In order to measure efficiency when both inputs and outputs are altered, one can employ the graph hyperbolic measure of technical efficiency:

$$TE_G = \min\{\alpha | (\alpha x, y/\alpha) \in T\}. \quad (14)$$

The idea is to simultaneously contract inputs and augment outputs by a factor of $\alpha > 0$ until the initial point (x_0, y_0) is projected onto the production frontier. The movement occurs along the hyperbolic path, which is depicted as the dashed line in *Figure 2*. The efficient point is then $(\alpha x_0, y_0 / \alpha)$.

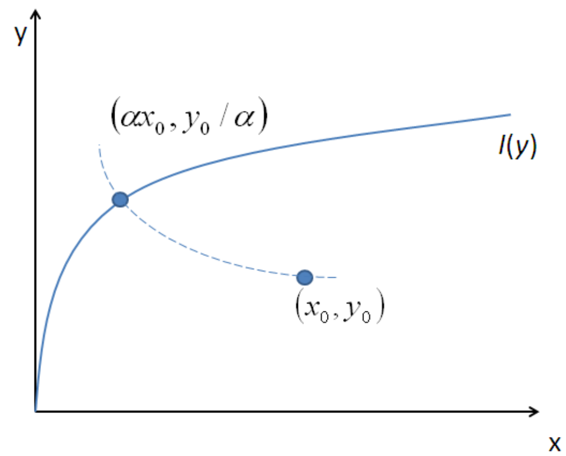

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Figure 2. **Graph Efficiency Measure**

Applications of the graph efficiency measure are not omnipresent as estimation thereof involves certain nonlinearities (Bogetoft, Otto, 2011). However, certain models require for such a non-radial movement in order to avoid infeasibilities.

The input- and output-oriented measures of efficiency can be generalized into the directional technology distance function (Färe *et al.*, 2008). In this case direction of improvement can be considered as a vector rather than a scalar (as in case of Shepard and Farrell distance functions). Thus, let $g=(g_x, g_y)$ be a directional vector with coordinates $g_x \in \Re_+^m$ and $g_y \in \Re_+^n$ and introduce the excess function:

$$E_D(x, y; g_x, g_y) = \max\left\{\beta \middle| \left(x_0 - \beta g_x, y_0 + \beta g_y\right) \in T\right\}. \tag{15}$$

Figure 3 illustrates exhibits this function.

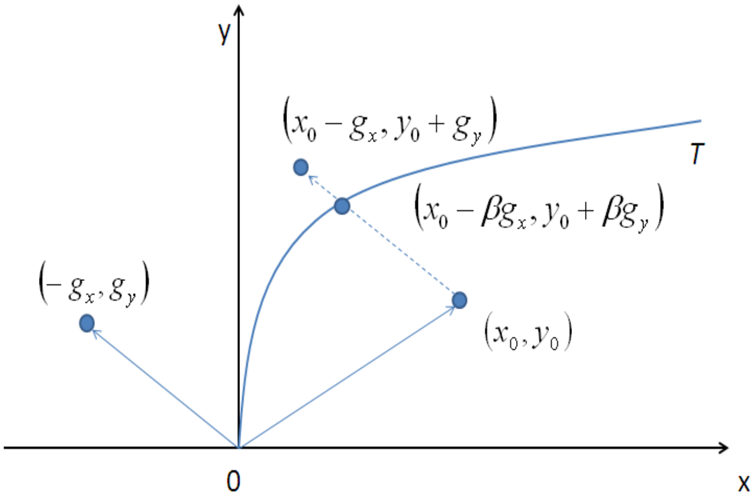

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Figure 3. **The Directional Technology Distance Function**

Technology is denoted by *T*, whereas the directional vector *g* is located in the fourth quadrant thus indicating that the directional movement towards the frontier is facilitated by simultaneously reducing inputs and increasing outputs. To be specific, inputs are scaled down by g_x, whereas outputs are increased by y_x. Thus the directional vector is transformed into $(-g_x, g_y)$ and added to the initial point (x_0, y_0). Addition of the two vectors means defining a parallelogram, the vertex whereof is given by $(x_0 - g_x, y_0 + g_y)$. Therefore, one will put the initial point on the efficiency frontier by maximizing *β*. By setting $(g_x, g_y) = (x, 0)$ and $(g_x, g_y) = (0, y)$ we would arrive at the input- and output-oriented distance functions, respectively. In addition one may choose $(g_x, g_y) = (x, y)$, $(g_x, g_y) = (\bar{x}, \bar{y})$, $(g_x, g_y) = (1,1)$, or optimize (g_x, g_y) to minimize distance to frontier technology.

It was already Farrell (1957) who described the two types of productive efficiency. Indeed, today these are referred to as technical efficiency and economic efficiency. The concepts and measures relating to technical efficiency were already discussed above. Economic efficiency can be further broken down into cost, revenue and profit efficiency with the latter encompassing the former two. Cost and revenue efficiencies are the products of technical and allocative efficiencies. Allocative efficiencies are estimated by the means of isocost or isorevenue curves. Profit efficiency encompasses the aforementioned cost and revenue efficiencies. We will further proceed by discussing the concept of cost efficiency, whereas revenue efficiency can be described in a similar vein.

Cost efficiency involves estimation of minimal costs which are defined as a product of input prices and quantities. Input prices can vary across the DMUs. Let the producers receive the vector of input prices $w = (w_1, w_2, ..., w_m) \in \Re^m_{++}$ and try to minimize cost. In this case, the isocost associated with the minimal cost level and technically feasible observation – cost frontier – is defined as:

$$c(y,w) = \min_x \{ w^T x | D_I(x,y) \geq 1 \}. \quad (16)$$

The obtained minimal cost can be used to estimate the Farrell measure of cost efficiency (CE):

$$CE(x,y,w) = c(y,w) / w^T x. \quad (17)$$

Producer's ability to adjust its input-mix in terms of the input prices is measured by input-allocative efficiency AE_I which is computed residually in terms of Eqs. 17 and 9:

$$AE_I(x,y,w) = CE(x,y,w) / TE_I(x,y). \quad (18)$$

This implies that cost efficiency can be decomposed into technical efficiency, which depends on the production set defined by input and output quantities, and allocative efficiency, which depend on input/output quantities and input. *Figure 4* depicts these measures.

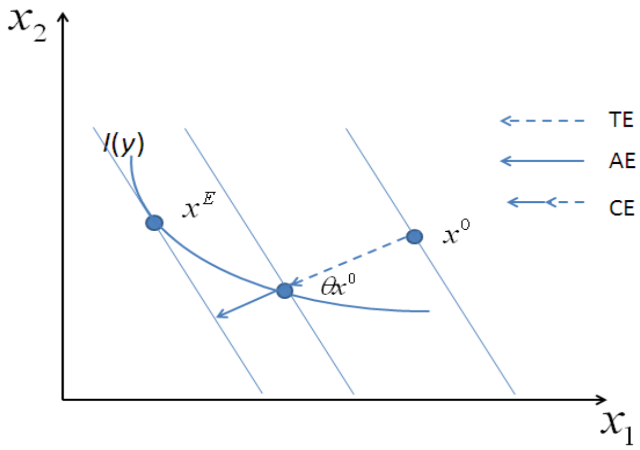

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Figure 4. **Cost Efficiency**

The three lines in *Figure 4* represent respective isocosts, namely $w^T x^E$, $w^T \theta x^0$, and $w^T x^0$ for points x^E, θx^0, and x^0, in that order. Here, the efficient point x^E is associated with the minimal cost level and thus the cost frontier defined by $c(y,w) = w^T x^E$. It is then possible to estimate the cost efficiency associated with point x^0 by considering the ratio $c(y,w)/w^T x^0 = w^T x^E / w^T x^0$ (cf. Eq. 17). The cost efficiency of x^0 can be further decomposed into technical efficiency $\theta^0 = \theta^0 x^0 / x^0 = w^T(\theta^0 x^0) / w^T x^0$ and allocative efficiency determined by the ratio $w^T x^E / w^T(\theta^0 x^0)$.

2. Frontier Models for Efficiency Estimation

As it was discussed in the preceding section, efficiency analysis relies on the two crucial components, viz. efficiency frontier (production frontier in the primal approach) and distance function. Indeed, there are many options to establish an efficiency frontier. First, these can be broken down into parametric and non-parametric methods (Murillo-Zamorano, 2004). Second, frontier techniques can be either deterministic or stochastic (Kuosmanen, Kortelainen, 2012). Third, frontier techniques can be either axiomatic or non-axiomatic (Afriat, 1972). Fourth, frontiers can be either average-practice or best-practice (Kuosmanen, Kuosmanen, 2009).

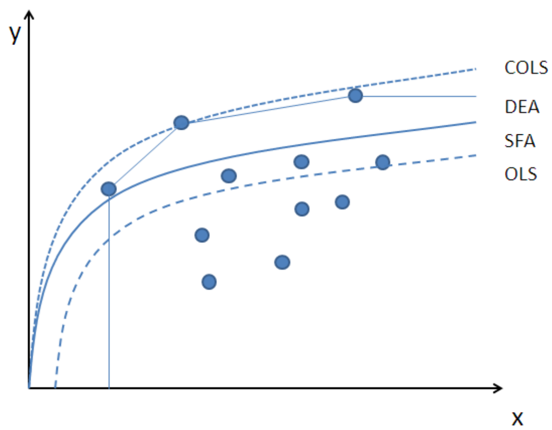
As regards parametric frontiers, these employ the pre-specified functional forms of the production frontiers (or cost frontiers, distance functions etc.). Estimation of the parameters of interest can be carried out econometrically (via Ordinary Least Squares (OLS), Maximum Likelihood or the like techniques) or by employing mathematical programming (linear programming, quadratic programming among other possibilities). Indeed, the estimated parameters can carry various kind of information: contribution of different inputs, cost types, shape of the underlying distributions of efficiency scores etc. (Bogetoft, Otto, 2011). Examples of parametric frontiers can be Stochastic Frontier Analysis (SFA), parametric programming (not to confuse with that kind of programming for sensitivity analysis), OLS-based frontiers among others. At the other end of spectrum, non-parametric frontiers require no *a priori* specification of the underlying functional form. Indeed, these frontiers are often assumed to be piecewise linear (or locally linear) ones. The major drawback of the latter approach is that the estimation of economic parameters becomes more complex and solutions are not uniquely defined for the strongly efficient points. The instances of non-parametric techniques include Data Envelopment Analysis (DEA), stochastic semi-nonparametric envelopment of data (StoNED). There exists an intermediary class of methods, namely semi-parametric techniques, which are based on kernel smoothing (non-parametric regression). These assume certain local functional forms, yet no specific form is needed for a frontier. See Czekaj (2013) for examples of these techniques.

Stochastic frontier models divide the overall distance between an observation and a frontier into stochastic and deterministic parts. Therefore, generally higher efficiency scores are obtained. However, certain assumptions regarding the underlying distribution of the efficiency scores are required. Examples of stochastic frontiers include SFA, StoNED, and some semi-parametric models with error-term decomposition. Bootstrapped DEA and chance-constrained (stochastic) DEA can also be considered as stochastic efficiency measures as they involve correction of the production frontiers. Deterministic models, on the other hand, attribute the whole distance between an observation and a frontier to either inefficiency or random noise. Accordingly, efficiency scores might be underestimated thanks to the influence of outliers. The deterministic models (from the viewpoint of efficiency analysis) are OLS models, corrected OLS (COLS), DEA, Free Disposal Hull (FDH).

Axiomatic frontier methods render theoretically sound production frontiers (in the primal approach). The resulting frontiers therefore satisfy certain axioms or non-axiomatic. For instance, DEA-based frontiers satisfy the axioms of convexity, monotonicity, and minimal extrapolation (Afriat, 1972). The StoNED model inherits these properties. On the other hand, most of the econometric models do not require for axiomatic technology. Usually, the numbers of cases of violations are reported. However, it is possible to impose certain restrictions upon these models in order to ensure that certain axioms are respected. For instance, Henningsen, Hennings (2009) presented a framework for imposing monotonicity in SFA.

Indeed, the very term "frontier model" implies we are looking at the best practice observations. The best-practice models are DEA, SFA, COLS and many others. In principle, these models account for inefficiency. In case inefficiency remains ignored, we arrive at the class of the average-practice models like OLS or Convex Non-parametric Least Squares.

Some of the aforementioned methods are compared in *Figure 5*. Several points can be made: Parametric methods (OLS, COLS, SFA) define continuous frontiers, whereas non-parametric model DEA offers a piece-wise approximation thereof. FDH would result in a non-convex frontier. DEA defines an empirical frontier, whereas the remaining ones are theoretical.



Source: designed by the author according to Bogetoft, Otto, 2011.

Figure 5. **Frontier Models**

COLS frontier (best-practice frontier) is that of OLS (average-practice frontier) shifted by a constant equal to the maximal error term. As a result, COLS attributes the whole error term to inefficiency, whereas OLS – to random noise. SFA assumes certain distribution of random error as well as inefficiency terms and thus defines an intermediary frontier.

Even though semi-parametric methods unite many appealing features of both parametric and non-parametric methods, they are still computationally cumbersome. In addition, program codes are not available for most of the "exotic" models. Therefore, SFA and DEA remain omnipresent tools for efficiency analysis. In the sequel, we will discuss these methods in a more detailed manner.

2.1 Data Envelopment Analysis

The simplest DEA model under assumption of VRS (Banker *et al.*, 1984) rests on the two basic assumptions, namely free disposability and convexity. The assumption of free disposability implies that the quantities of inputs and outputs can be freely disposed while keeping the resulting observation still feasible. In principle, this means that it is possible to maintain the same level of output by increasing input use, and, on the other hand, it is possible to decrease the output level while keeping input level fixed. For a given input-output bundle, these assumptions render a production possibility hull. The union of such hulls is a free disposable technology set. Specifically, let there be $k = 1,2,..., K$ DMUs with each of them featuring an input-output bundle (x^k, y^k). We can then define a free disposable technology as:

$$T = \left\{(x, y) \in \Re_+^m \times \Re_+^n \middle| \exists k \in \{1,2,..., K\} : x \geq x^k, y \leq y^k \right\}. \quad (19)$$

A graphic interpretation of the free disposable hull is presented in *Figure 6*. As one can note the resulting technology satisfies monotonicity, yet convexity is not maintained.

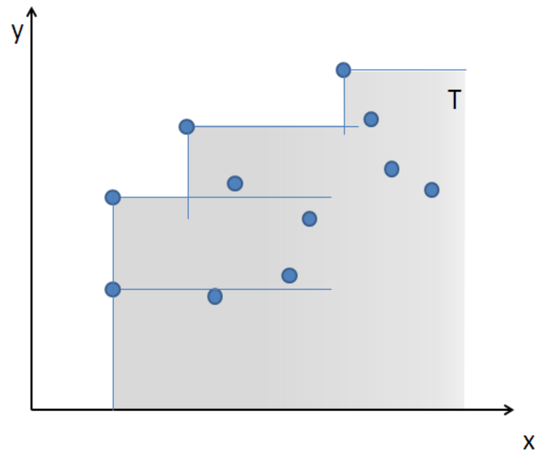


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Figure 6. **Free Disposable Hull**

The free disposal hull can be extended by imposing the assumption of convexity. The convexity assumption enables extrapolation of the feasible production plans assuming that any linear combination of the observed production plans (x^k, y^k) is also feasible. The convex technology set can be described in terms of input-output bundles and intensity variables as follows:

$$T = \left\{(x, y) \middle| x = \sum_{k=1}^{K} \lambda^k x^k, y = \sum_{k=1}^{K} \lambda^k y^k, \sum_{k=1}^{K} \lambda^k = 1, \lambda^k \geq 0, k = 1,2,..., K \right\}. \quad (20)$$

Assuming that the underlying technology is convex and free disposability, i. e. possessing properties of Eqs. 19-20, we can define the VRS technology:

$$T = \left\{(x, y) \middle| x \geq \sum_{k=1}^{K} \lambda^k x^k, y \leq \sum_{k=1}^{K} \lambda^k y^k, \sum_{k=1}^{K} \lambda^k = 1, \lambda^k \geq 0, k = 1,2,..., K \right\}. \quad (21)$$

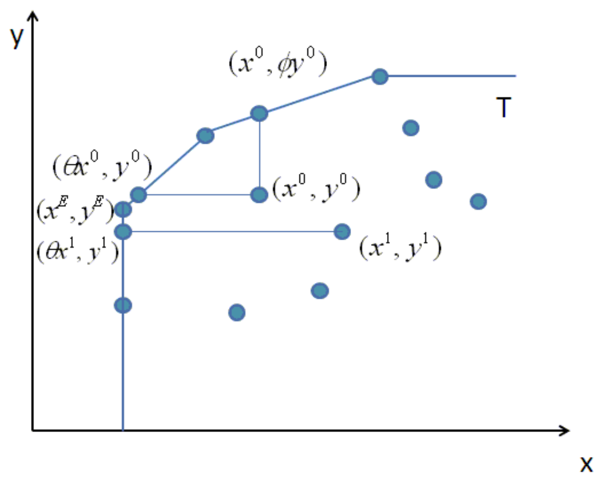
The resulting technology is depicted in Figure 7. Obviously, it includes all the feasible points given the original observations and assumptions regarding free disposability and convexity. The changes in assumptions of disposability would impact the shape of the parts of the frontier which are parallel to either of axes.

DEA is a non-parametric method suitable for measurement of efficiency of a decision–making unit (DMU) such as a firm or a public–sector agency (Ray, 2004). The modern version of DEA appeared in papers by A. Charnes, W.W. Cooper and E. Rhodes (Charnes *et al.*, 1978, 1981). Indeed, the latter papers presented the CRS models. Accordingly, suchlike DEA models are referred to as CCR models. First of all, the idea was to use the fractional form of DEA. In order to ensure its operationality, the fractional problem was transformed into multiplier program, which could be solved by means of the linear programming. Note that each linear programming problem has its dual problem. As for DEA, the dual CCR model is referred to as an envelopment program (Cooper *et al.*, 2007; Ramanathan, 2003).

In case DEA is employed to measure technical efficiency, it does not require imputing price data either for inputs or outputs. The latter feature makes it suitable for both private and public sectors. Assuming there exist K DMUs, each of them generating n outputs and consuming m inputs. Let $k = 1,2,...,t,...,K$, $j = 1,2,...,n$, and $i = 1,2,...,m$ be the indexes for DMUs, outputs, and inputs, respectively. For an arbitrarily chosen t–th DMU, the output-oriented technical efficiency is estimated via the multiplier DEA program:

$$\begin{aligned}
&\max_{\phi_t,\lambda_k} \phi_t \\
&\text{s. t.} \\
&\sum_{k=1}^{K} \lambda_k x_i^k \le x_i^t, \quad i = 1,2,...,n \\
&\sum_{k=1}^{K} \lambda_k y_j^k \ge \phi_t y_j^t, \quad j = 1,2,. \\
&\lambda_k \ge 0, \quad k = 1,2,...,K; \\
&\phi_t \text{ unrestricted.}
\end{aligned} \tag{22}$$

In Eq. 22, coefficients λ_k are intensity variables, i. e. they serve as weights of the peer DMUs defining the production frontier with respect to the t-th DMU. Please note that the latter model assumes CRS, which implies that all the observations are benchmarked to those featuring the highest productivity. To put it otherwise, DMUs can scale their input-output bundles radially without altering their scale efficiency and thus the overall technical efficiency (Ramanathan, 2003).



Source: designed by the author.

Figure 7. **Data Envelopment Analysis Model under VRS**

As the CRS constraint penalizes small and large producers in terms of technical efficiency and assumes no scale inefficiency. Therefore, Banker *et al.* (1984) offered the VRS model, which became known as the Banker, Charnes, Cooper (BCC) model. The VRS model is obtained by supplementing Eq. 22 with a convexity constraint $\sum_{k=1}^{K}\lambda_k = 1$. It is therefore possible to identify DMUs operating at the optimal scale (they feature full efficiency under CRS). The remaining DMUs exhibit scale inefficiency. Indeed, scale efficiency is measured as a ratio of CCR and BCC efficiency scores (they need to be treated as Farrell measures).

Figure 7 presents a graphical interpretation of the DEA model. The output-oriented measure, ϕ, defines the movement from (x^0, y^0) towards an efficient point (projection) on the frontier $(x^0, \phi y^0)$. Looking at another original observation, (x^1, y^1), we can depict the input-oriented analysis. Indeed, the latter point would be projected onto the efficiency frontier by minimizing its input use from x^1 to θx^1 (radial movement), while output is kept at the same level. Anyway, we would observe a slack in output, which equals to the difference between y^1 and y^E (non-radial movement).

Recent literature acknowledged various kinds of flaws associated to different DEA models. Accordingly various suggestions were offered (Liu *et al.*, 2013). Among the most important are the bootstrapping techniques for DEA (Simar, Wilson, 1998; Wilson, 2008; Odeck, 2009). Daraio, Simar (2007) presented the robust efficiency measures along with their conditional versions.

2.2 Stochastic Frontier Analysis

SFA is a parametric method for efficiency measurement. In its simplest form, it allows to define the production frontier for one output and multiple inputs technology. Further modifications, however, enable to relax this restriction. Unlike OLS and COLS, SFA models take into account both the efficiency term *u* and the error term *v*. The interaction among predicted and actual levels of output can be modelled in the spirit of Aigner *et al.* (1977) and Meeusen, van den Broeck (1977). The multiplicative form for the stochastic production frontier is given as:

$$y^k = f(x^k)TE_k e^{v_k}. \tag{23}$$

The base model after a log transformation becomes

$$y^k = f(x^k, \beta) + v^k - u^k$$
$$v^k \sim N(0, \sigma_v^2), u^k \sim N_+(0, \sigma_u^2), \tag{24}$$

Where N_+ denotes half-normal distribution truncated at the zero point. Greene (2008) presented a variety of possible distribution functions, namely truncated normal, exponential, and gamma. The Maximum Likelihood method is employed to estimate parameters *β*, *u*, and *v*. The firm-specific technical efficiency is computed as follows: $TE_k = \exp(-u)$.

The two functional forms are usually employed for SFA, viz. Cobb–Douglas (Cobb, Douglas, 1928) and Translog (Christensen *et al.*, 1971, 1973). The logged Cobb–Douglas production function has the following form:

$$\ln y_k = \ln\beta_0 + \sum_{i=1}^{m}\beta_i \ln x_i^k + v^k - u^k. \tag{25}$$

Translog (Transcendental Logarithmic Production Function) is a generalization of the Cobb–Douglas function:

$$\ln y_k = \beta_0 + \sum_{i=1}^{m}\beta_i \ln x_i^k + \frac{1}{2}\sum_{i=1}^{m}\sum_{l=1}^{m}\beta_{il}\ln x_i^k \ln x_l^k + v^k - u^k. \tag{26}$$

As one can note, production functions defined by Eqs. 25–26 can tackle only single–output technology only. To measure the productive efficiency and analyze the production technology, we can employ the Shepard distance functions (cf. Eqs. 8 and 11). Given both $D_I(x,y)$ and $D_O(x,y)$ are homogeneous of degree 1 in x and y, respectively, the following equations hold:

$$D_I^k(x^k, y^k) = x_m^k D_I^k\left(\frac{x^k}{x_m^k}, y^k\right), \tag{27}$$

$$D_O^k(x^k, y^k) = y_n^k D_O^k\left(x^k, \frac{y^k}{y_n^k}\right). \tag{28}$$

By logging both sides of Eqs. 27–28 and substituting $-\ln D_I^k = -\ln D_O^k = -u^k$, where u^k is the inefficiency term of the k-th DMU, we have:

$$\ln\left(\frac{1}{x_m^k}\right) = \ln D_I^k\left(\frac{x^k}{x_m^k}, y^k\right) - u^k, \tag{29}$$

$$\ln\left(\frac{1}{y_n^k}\right) = \ln D_O^k\left(x^k, \frac{y^k}{y_n^k}\right) - u^k. \tag{30}$$

The latter two equations can be evaluated by adding the error term v^k and specifying a SFA model. A translog function might be employed to approximate the input and output distance functions. By choosing (arbitrarily) certain input x_m we normalize the input vector and thus define a homogeneous translog input distance function:

$$\ln\left(\frac{1}{x_m^k}\right) = a_0 + \sum_{i=1}^{m-1} a_i \ln\frac{x_i^k}{x_m^k} + \sum_{j=1}^{n} b_j \ln y_j^k + \frac{1}{2}\sum_{i=1}^{m-1}\sum_{l=1}^{m-1}\alpha_{il}\ln\frac{x_i^k}{x_m^k}\ln\frac{x_l^k}{x_m^k} + \frac{1}{2}\sum_{j=1}^{n}\sum_{p=1}^{n}\beta_{jp}\ln y_j^k \ln y_p^k + \frac{1}{2}\sum_{i=1}^{m-1}\sum_{j=1}^{n}\gamma_{ij}\ln\frac{x_i^k}{x_m^k}\ln y_j^k + v^k - u^k. \tag{31}$$

Similarly, a translog output distance function is defined in the following way:

$$\ln\left(\frac{1}{y_n^k}\right) = a_0 + \sum_{i=1}^{m} a_i \ln x_i^k + \sum_{j=1}^{n-1} b_j \ln\frac{y_j^k}{y_n^k} + \frac{1}{2}\sum_{i=1}^{m}\sum_{l=1}^{m}\alpha_{il}\ln x_i^k \ln x_l^k + \frac{1}{2}\sum_{j=1}^{n-1}\sum_{p=1}^{n-1}\beta_{jp}\ln\frac{y_j^k}{y_n^k}\ln\frac{y_p^k}{y_n^k} + \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n-1}\gamma_{ij}\ln x_i^k \ln\frac{y_j^k}{y_n^k} + v^k - u^k. \tag{32}$$

Equations 31 and 32 imply that we only need to estimate a_1, a_2, ..., a_{m-1} and b_1, b_2, ..., b_{n-1}, respectively, whereas $a_m = 1 - \sum_{i=1}^{m-1} a_i$ and $b_n = 1 - \sum_{j=1}^{n-1} b_n$.

The similar computations are valid for the cost frontier. For instance, Greene (2008) presents the specification of a multiple–output tanslog cost function. After imposing its homogeneity it has the following form:

$$\ln\frac{C_k}{w_m} = \alpha_0 + \sum_{i=1}^{m-1}\alpha_i \ln\frac{w_i^k}{w_m^k} + \sum_{j=1}^{n}\beta_j \ln y_j^k + \frac{1}{2}\sum_{i=1}^{m-1}\sum_{l=1}^{m-1}\gamma_{il}\ln\frac{w_i^k}{w_m^k}\ln\frac{w_l^k}{w_m^k} + \frac{1}{2}\sum_{j=1}^{n}\sum_{p=1}^{n}\delta_{jp}\ln y_j^k \ln y_p^k + \frac{1}{2}\sum_{i=1}^{m-1}\sum_{j=1}^{n}\phi_{ij}\ln\frac{w_i^k}{w_m^k}\ln y_j^k + v^k + u^k, \tag{33}$$

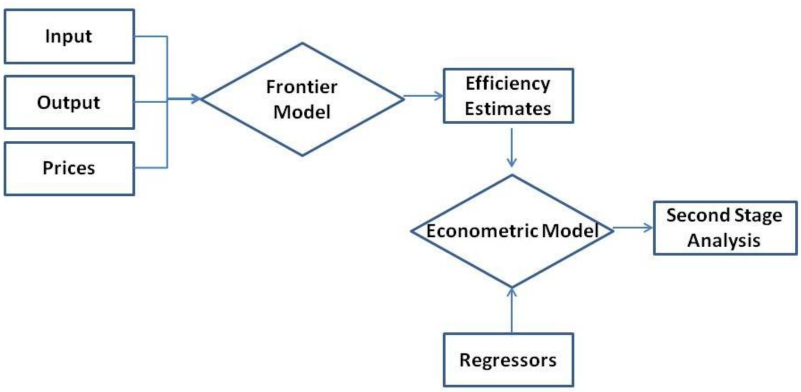
where C_k is the observed costs for the k-th DMU and w_i^k denotes price of the i-th input for the k-th DMU.

Indeed, many modifications are available for the SFA models. For instance, they can be modelled as equation systems with cost share equations. Furthermore, panel specifications can be employed. Finally, different assumptions regarding distributions of the efficiency scores can be made.

3. Developments in Methodology of the Agricultural Efficiency Research

Henningsen (2009) argued that agricultural efficiency is a complex feature intertwisted with various factors prevailing there. The latter factors are, for instance, labour intensity, farm structure, technology and investment, managerial skills, and profitability. Indeed, efficiency is expected to reflect the levels of productivity and profitability. Farm structure induces shifts in technology, labour intensity, and managerial skills as the larger a farm gets, the more financial and social resources it can accumulate. Labour intensity and labour opportunity costs are reciprocally related between themselves and impact the investments into advanced technologies. Furthermore, it is management skills, which play an important role on decisions regarding labour intensity and investments into technology. All the enumerated factors influence profitability, which, on its own right, is likely to determine farmers' decisions on keeping their business as a going concern and allocating their working time for non-agricultural activities. All in all, productive efficiency is dependent on multiple factors, which need to be taken into account for a sound analysis.

The general framework for efficiency analysis is presented in *Figure 8*. First, input, output, and price data are needed to estimate various types of efficiency by the means of frontier models. Second, the obtained efficiency estimates are treated as dependent variables for econometric model aimed at explaining the underlying causes of (in)efficiency. The latter model requires a set of explanatory variables – regressors – identifying certain sources of (in)efficiency. Particularly, these variables can be objective and subjective ones. Objective data may come from the same source as the data for the frontier model, namely databases, measurements etc. As for subjective data, they may be obtained by the means of questionnaire survey (see, for instance, Douarin, Latruffe, 2011).



Source: designed by the author.

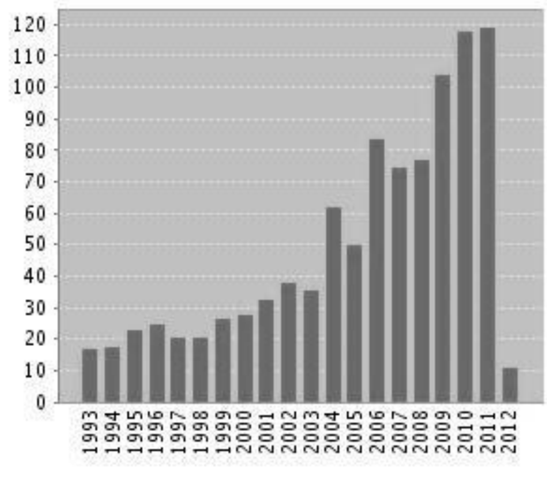
Figure 8. **The Conceptual Framework for the Frontier-Based Benchmarking**

The second stage (post-efficiency) analysis enables to identify specific factors influencing efficiency as well to quantify their impact. Therefore appropriate strategic management decisions can be offered, whereas the existing ones may undergo a thorough analysis.

The key elements of a benchmarking framework, namely frontier and econometric models, might be chosen from a set of various possible instruments. As it was discussed in the preceding section, the frontier models can be grouped into parametric and non-parametric ones with SFA and DEA representing these groups. The econometric model for second stage analysis can be, for instance, a logit or Tobit model, whereas panel data might be analyzed by the means of fixed or random effects models. Combinations of these options create certain patterns for efficiency research. We have thus performed a scientometric analysis aimed at identifying the current trends of frontier benchmarking in agriculture.

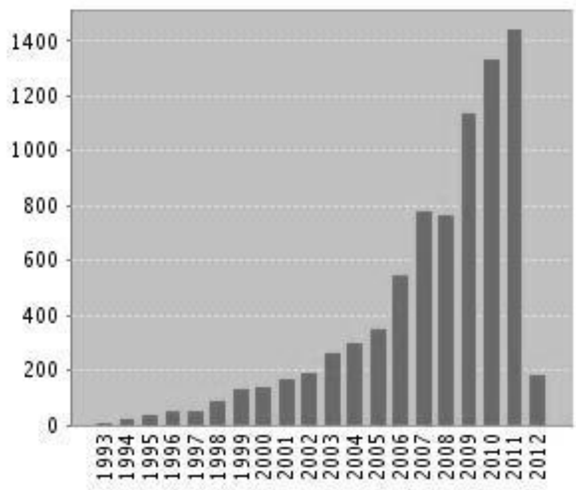
The scientometric analysis is based on data retrieved from the globally renowned database *Web of Science* (Thomson Reuters) which is usually employed for suchlike analyses (Zavadskas *et al.*, 2011). The aim of the scientometric research was to analyse the dynamics in number of citable items, namely articles, reviews, proceedings etc., related to the frontier efficiency measurement in agriculture. The research covers the period of 1990–2012 (as of March 2012).

The initial query was defined by setting publication topic equal to: (frontier OR stochastic frontier analysis OR data envelopment analysis) AND (agriculture OR farming). The latter query should identify the extent of manifestation of frontier measures across the current scientific sources. Of course, some papers are omitted thanks to usage of acronyms. As a result, the query returned 1011 publications. The number of released publications has been growing throughout the analysed period and approached some 120 publications per annum in 2011 (*Figure 9*). Meanwhile the number of citations has also been increasing and reached 8077 citations until 2012 with over 1400 citations per annum in 2011 (*Figure 10*). Frontier-based efficiency measurements in agriculture, therefore, can be considered as a rather prospective and expanding research area.



Source: Thomson Reuters.

Figure 9. **Published Items in Each Year**



Source: Thomson Reuters.

Figure 10. **Citations in Each Year**

Table 1 presents the main journals which constitute the basis for dissemination of the agricultural efficiency research results. The presented list implies that journals covering the areas of both agricultural economics and applied economics tend to publish these studies.

Queries on applications of SFA and DEA returned similar results, namely 272 and 230 publications, respectively. Therefore both of these methods are equally important for agricultural research. Meanwhile, the respective queries on application of the econometric instruments for second–stage analysis suggested Tobit regression being the most popular method (37 publications), whereas fixed effects (13 publications), random effects (7 publications), and logit (4 publications) models remained behind. Though, Simar and Wilson (2007) suggested using the double bootstrap procedure in lieu of the Tobit model in order to account for the underlying serial correlation of the DEA scores. Recently, Bădin *et al.* (2012) presented the framework for a fully non-parametric two-stage analysis, whereas Daraio and Simar (2014) proposed a double bootstrapping methodology for estimation of significance of the environmental variables.

Table 1. The main journals featuring publications on agricultural efficiency, 1990–2012

No.	Source Titles	Record Count	% of the total number
1.	Agricultural Economics	53	5.2
2.	Journal of Productivity Analysis	32	3.2
3.	American Journal of Agricultural Economics	29	2.9
4.	Applied Economics	27	2.7
5.	Journal of Agricultural Economics	22	2.2
6.	Agricultural Systems	20	2.0
7.	European Review of Agricultural Economics	18	1.8
8.	Ecological Economics	14	1.4
9.	African Journal of Agricultural Research	13	1.3
10.	Journal of Dairy Science	13	1.3

Source: designed by the author according to Thomson Reuters.

We will review some recent studies on frontier measures of agricultural efficiency in order to reveal the concrete manifestations of frontier efficiency measurement as well as second stage analysis. Latruffe *et al.* (2004) analysed the efficiency of crop and livestock farming in Poland by the means of SFA and DEA. SFA analysis was carried out by employing efficiency effects model (Battese, Coelli, 1995) relating the observed inefficiencies with a pre-defined set of efficiency variables. Thus, the second stage analysis can be implemented simultaneously with estimation of the SFA model. The DEA analysis, however, was supplemented by the second stage analysis, namely Tobit regression. The Cobb-Douglas production function was employed for SFA to regress the total output in value against utilized agricultural area (UAA), annual work units (AWU), depreciation plus interests, and intermediate consumption. Indeed, the latter four variables stand for land, labour, capital, and variable input factors. The following variables were chosen as the factors of inefficiency: total output, share of hired labour, degree of market integration (i. e. the ratio of total revenue over total output), soil quality index, and farmer’s age. The Tobit model for DEA included variables defining ratios between certain inputs as well as the inefficiency determinants from SFA model.

Bojnec, Latruffe (2008) analysed performance of the Slovenian farms by the means of both DEA and SFA. The allocative and economic efficiencies were also estimated. The cluster analysis was employed to classify the analysed farming types into relatively homogeneous groups, however there was no second state analysis performed. Akinbode *et al.* (2011) employed the same SFA with efficiency effects model for estimation of technical efficiency. Moreover, the cost function was specified to estimate allocative and economic efficiency. The variation in the latter two efficiencies was explained by employing Tobit model. The same methodological framework was implemented by Samarajeewa *et al.* (2012) to analyse beef cow/calf farming in Canada. Lambarra, Kallas (2010) implemented efficiency effects SFA model when estimating impact of Less Favoured Area (LFA) payments on farming efficiency. The two production functions therefore were defined for farms receiving LFA payments and for those not receiving payments. The random effect Tobit model was employed for the whole sample with an additional dummy variable identifying absorption of these payments.

The study of Asmild, Hougaard (2006) focuses on efficiency of Danish pig farms from the ecological and economic viewpoints. The directional DEA was applied to estimate the efficiency and possible improvements. Rasmussen (2011) employed the input distance function to estimate efficiency of the Danish pig, dairy, and crop farms. These functions were also used to estimate the optimal operation scale for respective farming type. Nauges *et al.* (2011) presented the state-contingent stochastic production function to assess land distribution under different plant species regarding the weather conditions (i.e. states). Karagiannis, Sarris (2005) applied SFA to measure scale efficiency in Greek tobacco farms. The second-stage analysis aimed to identify the drivers of scale efficiency. Kumbhakar *et al.* (2014) employed a range of panel SFA methods with different specifications of inefficiency. Fousekis *et al.* (2014) utilised the conditional efficiency measures to non-parametrically estimate the impact of factors of efficiency in Greek olive farms.

A meta-regression analysis including 167 farm level technical efficiency studies of developing and developed countries was undertaken by Bravo-Ureta *et al.* (2006). The econometric results implied lower TE scores are obtained by employing SFA as opposed to those obtained by DEA. In addition, deterministic parametric models are also likely to populate lower efficiency scores if compared to SFA. Production functions (the primal approach) were estimated most frequently. The study showed that animal farming features higher TE if compared to crop farming. It was also concluded that farming in Western Europe and Oceania is likely to feature higher levels of TE. Noteworthy, another meta-study revealed a negative relationship between subsidies and efficiency across the European countries (Minviel, Latruffe, 2014).

Efficiency of Lithuanian agricultural sector has not been widely analysed. Indeed, the current literature on the issue mainly employs non-parametric methodology. Rimkuvienė *et al.* (2010) carried out an international comparison of farming efficiency. The research relied on the Farm Accountancy Data Network aggregates. Baležentis, Valkauskas (2013) utilised the DEA to perform a quantitative analysis of returns to scale. As a result, economically optimal size was estimated for crop, livestock and mixed farms. Baležentis *et al.* (2014) proposed a fully non-parametric framework for two-stage analysis and employed it to a sample of Lithuanian family farms. Furthermore, the patterns of dynamics of the efficiency scores were revealed by the virtue of the fuzzy clustering. Hougaard, Baležentis (2014) proposed a fuzzy FDH model. Given agricultural producers are subject to various kinds of uncertainties, the fuzzy data were used to represent the performance of the producers throughout 2004-2009. Baležentis (2014) applied the bias-corrected Malmquist indices to describe the technology changes prevailing in Lithuanian family farms. Suchlike analysis enables to identify changes in marginal rates of technical substitution and thus possible changes in the input-mix structure. Douarin, Latruffe (2011) estimated farming efficiency and impacts of the European Union Single Area Payments in Lithuania. Indeed, efficiency analysis was supplemented with a questionnaire survey. As a result, the possible decisions and their effect upon efficiency were estimated.

To conclude, analysis of the productive efficiency of Lithuanian agriculture is still a promising area for empirical researches. The literature survey indicates that there is a need for application of parametric techniques. In addition, most of the attention was paid to family farms, whereas corporate farms remained aside.

Conclusions

The carried out analysis suggests that frontier benchmarking in agriculture is a robustly developing branch of science. To be specific, the number of publications released per year on frontier benchmarking in agriculture has increased sixfold since early 1990s. Indeed, both data envelopment analysis and stochastic frontier analysis are equally important instruments for estimating productive efficiency. It is the tobit model that can be considered as the most popular method for the second stage analysis, yet the double bootstrap procedure is to be employed in order to avoid the flaws associated with the serial correlation of the DEA scores.

The Lithuanian agricultural sector, however, is not sufficiently analysed by the means of the frontier techniques. The Lithuanian agricultural sector still facing the consequences of post-communist transformations should be analysed by employing the discussed two-stage frontier benchmarking framework in order to fathom the underlying trends in productivity, efficiency, and farming decisions. The discussed methods and research frameworks would certainly increase the effectiveness of the strategic management decisions.

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APIE ŽEMĖS ŪKIO EFEKTYVUMO VERTINIMĄ – APŽVALGA

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SANTRAUKA

Tyrimo tikslas – aptarti teorinius efektyvumo matavimo pagrindus ir atlikti efektyvumo vertinimo raiškos žemės ūkio ekonomikos tyrimuose apžvalgą. Straipsnyje pristatoma efektyvumo samprata ir jos matavimo koncepcijos, taip pat matematiniai efektyvumo vertinimo modeliai. Ypatingas dėmesys skiriamas dviem plačiai taikomiems ribiniams metodams – duomenų apgaubties analizei ir stochastinei ribinei analizei. Siekiant įvertinti ribinių metodų taikymo žemės ūkio efektyvumo tyrimuose tendencijas, buvo atlikta mokslometrinė analizė. Taip pat apžvelgtos naujausios publikacijos, susijusios su nagrinėjamu klausimu. Tyrimas parodė, kad Lietuvos žemės ūkio sektoriaus gamybinis efektyvumas dar nėra pakankamai nagrinėtas taikant ribinius metodus. Aptarti metodai ir sistemos leistų padidinti strateginio valdymo sprendimų veiksmingumą.

REIKŠMINIAI ŽODŽIAI: efektyvumas, žemės ūkis, ribiniai metodai, duomenų apgaubties analizė, stochastinė ribinė analizė.