LITHUANIAN INSTITUTE OF AGRARIAN ECONOMICS

EFFICIENCY IN THE LITHUANIAN AGRICULTURAL SECTOR: APPLICATIONS OF THE NON-PARAMETRIC AND PARAMETRIC MEASURES

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SUMMARY

The study **aims** at measuring and analyzing the productive efficiency of the Lithuanian family farms and identifying the related policy implications. The following **tasks** are, therefore, set: (i) to present the research methodology for efficiency analysis, (ii) to estimate the technical efficiency by the means of the non-parametric techniques, (iii) to estimate the technical efficiency by the means of the parametric techniques, and (iv) to quantify the impact of the efficiency effects.

The study estimated the technical, allocative, and cost efficiency of the Lithuanian family farms. Furthermore, the stochastic frontier analysis was employed to analyse the dynamics of the total factor productivity and output elasticities. Noteworthy, these measures have not been analysed in the Lithuanian scientific literature ever before.

The study is therefore **structured** as follows. The first two sections deal with the general preliminaries to efficiency analysis. Section 1 presents the definitions and measures of the productive efficiency. Section 2 presents the main mathematical models for implementation of efficiency measures, namely data envelopment analysis and stochastic frontier analysis. The remaining two sections deal with agricultural efficiency research. Specifically, Section 3 presents results of the scientometric analysis and a literature review on frontier benchmarking in agriculture. Section 4 then presents some specific techniques and results of the empirical analysis of the efficiency patterns in the Lithuanian agricultural sector.

Keywords: efficiency, total factor productivity, data envelopment analysis, stochastic frontier analysis, family farms, direct payments.

SANTRAUKA

LIETUVOS ŽEMĖS ŪKIO SEKTORIAUS EFEKTYVUMO ANALIZĖ TAIKANT NEPARAMETRINIUS IR PARAMETRINIUS METODUS

Tyrimo tikslas – apibendrinant Lietuvos žemės ūkio sektoriaus efektyvumo tyrimus, įvertinti Lietuvos žemės ūkio sektoriaus gamybinį efektyvumą ir nustatyti perspektyvias žemės ūkio politikos tobulinimo kryptis. Tyrimo uždaviniai: 1) literatūros apžvalga ir ribinių metodų aptarimas; 2) Lietuvos ūkininkų ūkių techninio ir ekonominio efektyvumo įvertinimas neparametriniais metodais; 3) Lietuvos ūkininkų ūkių techninio ir ekonominio efektyvumo įvertinimas parametriniais metodais; 4) efektyvumo veiksnių poveikio vertinimas.

Darbe aptarti teoriniai efektyvumo matavimo pagrindai ir atlikta efektyvumo vertinimo raiškos žemės ūkio ekonomikos tyrimuose apžvalga. Darbe pristatoma efektyvumo samprata ir jo 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. Paskutinėje darbo dalyje pristatomas žvalgomasis tyrimas – neparametrinio Lietuvos ūkininkų ūkių veiklos efektyvumo vertinimo rezultatai.

Empirinis tyrimas remiasi Ūkių apskaitos duomenų tinklo respondentinių ūkių rodikliais, apibūdinančiais 200 ūkininkų ūkių veiklą 2004–2009 metais. Taikant duomenų apgaubties analizės metodą nustatyta, kad tyrimo laikotarpiu vidutinis techninis ūkio efektyvumas siekė 65,8 proc., paskirstymo efektyvumas siekė 70,5 proc., o ekonominis efektyvumas – 46 proc. Antrojo etapo analizei taikyti regresinės analizės modeliai: tobit modelis naudotas efektyvumo rodiklio priklausomybei nuo pasirinktų ūkio charakteristikų vertinimui, o logit modelis susiejo minėtas charakteristikas su efektyvumo pokyčiais. Minėti modeliai leidžia teigti, kad efektyviau veikė stambieji ir ekologiniai ūkiai. Minėtieji ūkiai taip pat turėjo daugiau galimybių padidinti efektyvumą. Stochastinės ribinės analizės pagalba buvo įvertinta stochastinė gamybos funkcija ir apskaičiuoti techninio efektyvumo rodikliai, gamybos elastingumai ir bendrojo produktyvumo pokyčiai. Pastaruoju metodu gauti rezultatai rodo, kad ūkininkų ūkių veiklos efektyvumas siekė 80 proc., o efektyviausiai veikė gyvulininkystės ūkiai. Atsižvelgiant į gamybos elastingumus, produktyviausias gamybos veiksnys buvo tarpinis vartojimas, o ilgalaikis turtas buvo nuo kelis kartus mažiau produktyvus. Žemės, kaip gamybos veiksnio, produktyvumas buvo pats mažiausias iš nagrinėtųjų. Darbe taip pat aptarti bendrojo produktyvumo pokyčiai. Efektyvumo įverčių, gautų duomenų apgaubties analizės ir stochastinės ribinės analizės pagalba, palyginimas parodė, kad tiek parametrinis, tiek neparametrinis metodai atskleidė tuos pačius efektyvumo dėsningumus Lietuvos ūkininkų ūkiuose.

Raktažodžiai: efektyvumas, bendrasis produktyvumas, duomenų apgaubties analizė, stochastinė ribų analizė, ūkininkų ūkiai, tiesioginės išmokos.

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ABBREVIATIONS

CAP –	Common Agricultural Policy
CRS –	Constant Returns to Scale
DEA –	Data Envelopment Analysis
DMU –	Decision Making Unit
DRS –	Decreasing Returns to Scale
EC –	Efficiency Change
EU –	European Union
FADN –	Farm Accountancy Data Network
IRS –	Increasing Returns to Scale
NIRS –	Non-increasing Constant Returns to Scale
SFA –	Stochastic Frontier Analysis
TC –	Technical Change
TE –	Technical Efficiency
TFP –	Total Factor Productivity
VRS –	Variable Returns to Scale

INTRODUCTION

The foremost goal of any economic research is to ensure the proper allocation of resources and thus achieve social and economic welfare (Latruffe, 2010). In order to identify the most promising practice one needs to employ respective methodology. 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 and Boone (2009) benchmarking can create motivation for change; provide a vision for what an organization can look like after change; provide data, evidence, and success stories for inspiring change; identify best practices for how to manage change; and create a baseline or yardstick by which to evaluate the impact of earlier changes.

Reasonable strategic decision making requires an integrated assessment of the regulated sector. The agricultural sector is related to voluminous public support as well as regulations. The application of benchmarking, thus, becomes especially important when fostering sustainable agricultural development. Furthermore, productive efficiency gains might result into lower costs as well as greater profit margins for the producer and better prices for the participants in 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 typically own land and live on their farms, therefore the standard 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, this is not the case and the ideal behaviour can be described only by analyzing the actual data, i. e. by the means of 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.

It is due to Alvarez and Arias (2004) and Gorton and Davidova (2004) that frontier techniques are the most widely applied methods for efficiency measurement in agriculture. Indeed, the frontier methods can be grouped into parametric and non-parametric ones. For instance, Aysan *et al.* (2011) employed stochastic frontier analysis for assessment of the Turkish banking sector. Rasmussen (2011) employed the same method for analysis of the Danish farms. Chou *et al.* (2012) employed stochastic frontier analysis to measure performance of the IT capital goods sectors across OECD countries. Zhan (2012) analysed the properties of different stochastic frontier specifications. Aristovnik (2012) utilized the non-parametric technique, namely data envelopment analysis, to analyse the efficiency of R&D expenditures in some European Union Member States. Bojnec and Latruffe (2011) as well as Davidova and Latruffe (2007) applied data envelopment analysis to assess the performance of Slovenian and Czech farms, respectively. Bilgin *et al.* (2012) attempted to research into the Chinese firm performance by the means of the deterministic Cobb-Douglas frontier. Latruffe *et al.* (2004) applied both stochastic frontier analysis and data envelopment analysis to analyse the technical efficiency of the Polish farms. Rahman and Salim (2013) employed the Fare-Primont index to analyse the TFP growth in the Bangladesh agriculture.

Topicality of the research. Family farming has been reinvigorating in Lithuania since early 1990s when the collective farming system was deconstructed. Since then the Lithuanian farming system has undergone many economic, structural, and institutional reforms. Year 2004 marks the accession to the European Union (EU) which is related to the Common Agricultural Policy. The Lithuanian farming system, however, is not fully developed yet. In terms of the utilized agricultural area, the average Lithuanian farm expanded from 9.2 ha up to 13.7 ha during 2003–2010, whereas the total utilized agricultural area increased by some 10% and the number of agricultural holdings decreased by 27% from 272 thousand down to less than 200 thousand (Statistics Lithuania, 2011). Indeed, the number of the smallest farms has decreased and these adjustments lead to a farm structure which is similar to that of the European countries. There is, however, a substantial area of state-owned or abandoned land which can be employed for the agricultural activities in the future. Therefore it is important to analyze the farming efficiency which identifies many factors influencing farmers' decisions.

The research was motivated by both importance of efficiency measurement and lack of suchlike studies in the Lithuanian context. 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). To be specific, some 2.287 billion EUR were assigned under the Lithuanian Rural Development Programme for 2007–2013. 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 analyze the farming efficiency in Lithuania (Rimkuvienė *et al.*, 2010, Baležentis, Baležentis, 2011; Baležentis, Kriščiukaitienė, 2012). Moreover, these papers were focused on diachronic analysis or different farming types were analyzed by employing single–period data. Another issue to be tackled is post–efficiency analysis.

The study **aims** at measuring and analyzing the productive efficiency of the Lithuanian family farms and identifying the related policy implications. The following **tasks** are, therefore, set: (i) to present the research methodology for efficiency analysis, (ii) to estimate the technical efficiency by the means of the non-parametric techniques, (iii) to estimate the technical efficiency by the means of the parametric techniques, and (iv) to quantify the impact of the efficiency effects.

The study estimated the technical, allocative, and cost efficiency of the Lithuanian family farms. Furthermore, the stochastic frontier analysis was employed to analyse the dynamics of the total factor productivity and output elasticities. Noteworthy, these measures have not been analysed in the Lithuanian scientific literature ever before.

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1. DEFINITIONS AND MEASURES OF EFFICIENCY

Instead of defining the efficiency as the ratio between outputs and inputs, we can describe it as a distance between the quantity of input and output, and the quantity of input and output that defines a frontier, the best possible frontier for a firm in its cluster (Daraio, Simar, 2007).

The very term of efficiency was initially defined by Koopmans (1951). Koopmans offered the following definition of an efficient decision making unit (DMU): *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*. Due to similarity to the definition of Pareto efficiency, the former is called Pareto–Koopmans Efficiency. Such a definition enabled to distinguish efficient and inefficient DMUs, however it did not offer a measure to quantify the level of inefficiency specific to a certain DMU.

Thus Debreu (1951) discussed the question of resource utilization and introduced the measure of productive efficiency, namely coefficient of resource utilization. Debreu's measure is a radial measure of technical efficiency. Radial measures focus on the maximum feasible equiproportionate reduction in all variable inputs for an input-conserving orientation, or the maximum feasible equiproportionate expansion of all outputs for an output-augmenting orientation (Daraio, Simar, 2007; Fried *et al.*, 2008).

Finally, Farrell (1957) summarized works of Debreu (1951) and Koopmans (1951) thus offering frontier analysis of efficiency and describing two types of *economic efficiency*, namely *technical efficiency* and *allocative efficiency* (indeed, a different terminology was used at that time). It is worth to note, that the seminal paper of Farrel (1957) was dedicated to analysis of agricultural production in the United States. The concept of technical efficiency is defined as the capacity and willingness to produce the maximum possible output from a given bundle of inputs and technology, whereas the allocative efficiency reflects the ability of a DMU to use the inputs in optimal proportions, considering respective marginal costs (Kalirajan, Shand, 2002). However, Farrell (1957) noted that price information is rather hard to tackle in a proper way, thus technical efficiency became a primal measure of the productive efficiency.

Besides, the two other types of efficiency can be defined, viz. scale and structural efficiency. Scale efficiency measures the extent to which outputs increase due to increase in input. Farrel (1957) and later Charnes, Cooper and Rhodes (1978) employed the most restrictive constant returns to scale (CRS) assumption. The latter assumption was relaxed by Banker, Charnes and Cooper (1984), who also pointed out that scale efficiency is related to variable returns to scale (VRS) efficiency (pure technical efficiency) and CRS technical efficiency. The structural efficiency is an industry level concept describing the structure and performance of certain sector which is determined by performance of its firms. Indeed, one sector can be structurally efficient than another in case its firms are operating closer to the efficiency frontier. For instance, one can define hypothetic average values for several sector and compute efficiency scores for them thus assessing differences in structural efficiency across these sectors.

In order to relate the Debreu–Farrel measures to the Koopmans definition, and to relate both to the structure of production technology, it is useful to introduce some notation and terminology (Fried *et al.*, 2008). Let producers use inputs $x=(x_1,x_2,...,x_m)\in\Re_+^m$ to produce outputs $y=(y_1,y_2,...,y_n)\in\Re_+^n$. Production technology then can be defined in terms of the production set:

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

Thus, Koopmans efficiency holds for an input-output bundle $(x,y)\in T$ if, and only if, $(x',y')\notin T$ for $(-x',y')\geq(-x,y)$.

Technology set can also be represented by input requirement and output correspondence sets, respectively:

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

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

The isoquants or efficient boundaries of the sections of *T* can be defined in radial terms as follows (Farrel, 1957). Every $y\in\Re_+^n$ has an input isoquant:

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

Similarly, every $x\in\Re_+^m$ has an output isoquant:

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

In addition, DMUs might be operating on the efficiency frontier defined by Eqs. 4–5, albeit still use more inputs to produce the same output if compared to another efficient DMU. In this case the former DMU experiences a slack in inputs. The following subsets of the boundaries *I*(*y*) and *O*(*x*) describe Pareto-Koopmans efficient firms:

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

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

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

There are two types of efficiency measures, namely Shepard distance function, and Farrel distance function. These functions yield the distance between an observation and the efficiency frontier. Shepard (1953) defined the following input distance function:

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

Here $D_I(x,y) \geq 1$ for all $x \in I(y)$, and $D_I(x,y) = 1$ for $x \in isoI(y)$. The Farrel input-oriented measure of efficiency can be expressed as:

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

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

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

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

Similarly, the following equations hold for the output-oriented measure:

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

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

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

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

Note that the Farrel measures, TE_I and TE_O, are homogeneous of degree −1 in inputs and outputs, respectively; whereas the Shepard measures, D_I and D_O, are homogeneous of degree +1 in inputs and outputs, respectively.

Figure 1 depicts the two efficiency measurement approaches discussed above, namely input- and output-oriented. Initial input-output bundle (x_0, y_0) is projected into efficiency frontier T by (i) reducing inputs and thus achieving an efficient point $(\theta x_0, y_0)$ or (ii) augmenting outputs and thus achieving an efficient point $(x_0, \phi y_0)$. Noteworthy, Figure 1 presents a production frontier, for output quantity is related to input quantity there. In case the two input (output) quantities were related, one would have an isoquant (a transformation curve) as well as the implicit assumption of constant returns to scale.

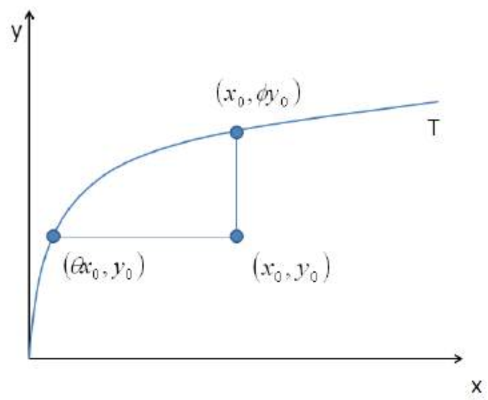

Fig. 1. Technical efficiency measurement in terms of the Farrel measures

Besides the discussed non-directional efficiency measures there exists a class of directional efficiency measures. Whereas the former methods analyse equiproportional scaling of either inputs or outputs, the directional measures consider both of these alterations simultaneously.

One of the initial suggestions of the directional efficiency measurement is the graph hyperbolic measure of technical efficiency:

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

By simultaneously reducing inputs and expanding outputs with α>0 we move the initial point (x_0, y_0) along the hyperbolic curve (the dashed line in Figure 2) until it reaches the efficiency frontier at the point $(\alpha x_0, y_0 / \alpha)$.

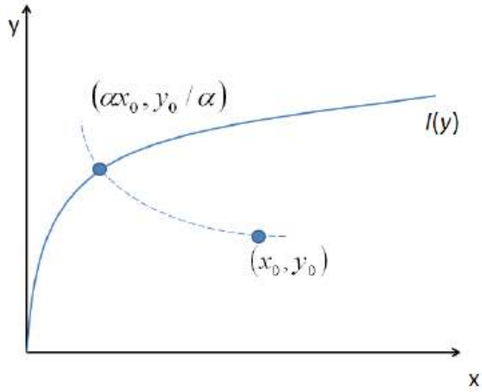

Fig. 2. The graph efficiency measure

The graph efficiency measure, however, is seldom employed due to the non-linearities involved (Bogetoft, Otto, 2011).

The previously discussed Shepard 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 Farrel distance functions). Thus, let $g = (g_x, g_y)$ be a direction vector with $g_x \in \Re_+^m$ and $g_y \in \Re_+^n$ and introduce the excess function:

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

Figure 3 illustrates this function.

Technology is denoted by *T*, whereas the directional vector *g* is in the fourth quadrant indicating that the inputs are to be contracted and outputs augmented simultaneously. To be specific, inputs are scaled down by g_x, whereas outputs are increased by g_y. 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.

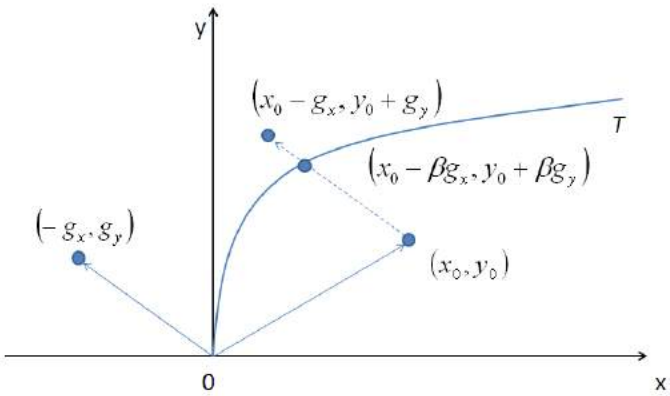

Fig. 3. The directional technology distance function

As it was already said, Farrel (1957) defined the two types of efficiency, which are known as technical and economic efficiency. The technical efficiency and its measures were described above. The economic efficiency is divided into cost, revenue and profit efficiency. For each of the three measures, a respective frontier is established. Here we focus solely on cost efficiency. However, revenue efficiency is a straightforward modification of the cost efficiency.

Assume that producers face input prices $w = (w_1, w_2, ..., w_m) \in \Re^m_{++}$ and seek to minimize cost. Thus, a minimum cost function—cost frontier—is defined as:

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

Then a measure of cost efficiency (CE) is defined as the ratio of the minimum cost to the actual cost:

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

A measure of input-allocative efficiency AE_I is obtained by employing Eqs. 7 and 9:

$$AE_I(x, y, w) = CE(x, y, w) / TE_I(x, y). \tag{18}$$

Thus, cost efficiency can be expressed as a product of technical efficiency and cost allocative efficiency. Figure 4 depicts these measures.

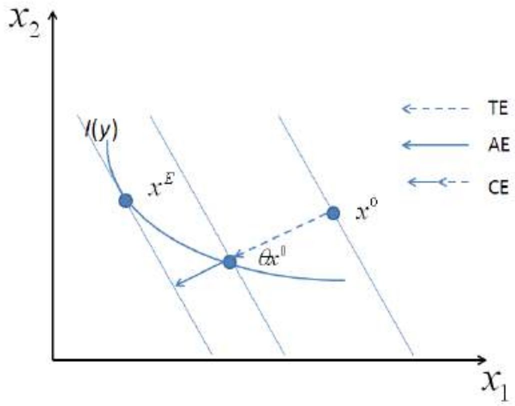

Fig. 4. The concept of cost efficiency

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 minimizes cost and thus defines the cost frontier $c(y,w) = w^T x^E$. The cost efficiency of the point x^0 is then given by 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

The discussed efficiency frontier can be established by employing different computation techniques. As Murillo-Zamorano (2004) pointed out, these can be classified into parametric and non-parametric methods.

The parametric frontier methods rely on econometric inference and aims at estimating parameters for pre-defined exact production functions. These parameters may refer, for instance, to the relative importance of different cost drivers or to parameters in the possibly random noise and efficiency distributions (Bogetoft, Otto, 2011). The parametric frontier methods can be further classified into deterministic and stochastic ones. The two deterministic frontier models, namely Ordinary Least Squares (OLS) and Corrected Ordinary Least Squares (COLS), attribute the distance between an observation and the efficiency frontier to statistical noise or inefficiency, respectively. The stochastic parametric method—Stochastic Frontier Analysis (SFA)—explains the gap between an observation and the efficiency frontier in terms of both inefficiency and random errors.

On the other side, non-parametric frontier methods aim at establishing an empirical production frontier. Specifically, the empirical production frontier (surface) is defined by enveloping linearly independent points (observations) and does not require subjective specification of the functional form. Therefore the non-parametric models are easier to be implemented. It is the deterministic non-parametric frontier methods that do not allow statistical noise and thus explains the whole distance between the observation and production frontier by inefficiency. Data Envelopment Analysis (DEA) and Free Disposable Hull (FDH) are the two widely renowned non-parametric deterministic models. The stochastic non-parametric methods accounts for the statistical noise by correcting the initial observations and, thus, the efficiency frontiers. Bootstrapped DEA, chance-constrained (stochastic) DEA, stochastic semi-non-parametric envelopment of data (STONED) can be given as the examples of the latter class of the frontier methods.

The following Figure 5 depicts differences between some of the discussed methods. As one can note, the 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. To be precise, the DEA frontier is not completely devoid of assumptions on its functional form. Indeed, it is considered to be locally linear one. Given DEA and FDH frontiers are defined empirically, they do include at least one observation, which is then considered as an efficient one. The same applies for the COLS frontier. In case of the OLS and SFA frontiers, no observations are considered to be fully efficient.

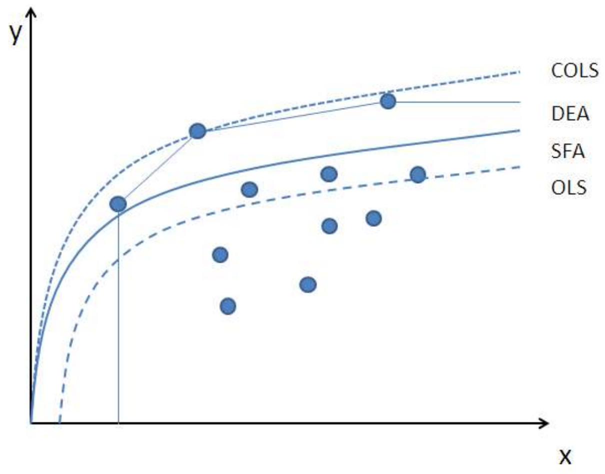

Fig. 5. Parametric and non-parametric frontier models

COLS frontier is based on the OLS one and shifted by a constant equal to the maximal error term so that the resulting error term would satisfy $e \geq 0$. SFA assumes certain distribution of random error as well as inefficiency terms and thus defines an intermediary frontier.

Indeed, SFA and DEA are the two seminal methods for, respectively, parametric and non-parametric analysis. These methods are to be discussed throughout the remaining part of the study.

2. 1. Data envelopment analysis

DEA specifies the efficiency frontier with respect to the two assumptions, namely free disposability and convexity. The assumption of the free disposability means that we can dispose of unwanted inputs and outputs. First, if we can produce a certain quantity of outputs with a given quantity of input, then we can also produce the same quantity of outputs with more inputs. Second, if a given quantity of inputs can produce a given quantity of outputs, then the same input can also be used to produce less output (Bogetoft, Otto, 2011). By combining these two assumptions we arrive at the free disposability of inputs and outputs. The technology related to free disposability assumption is called the free disposable hull. Assume there are $k = 1,2,\ldots,K$ firms each possessing a certain input-output bundle (x^k, y^k), then the free disposable hull is defined as

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

An graphic interpretation of the free disposable hull is presented in Figure 6.

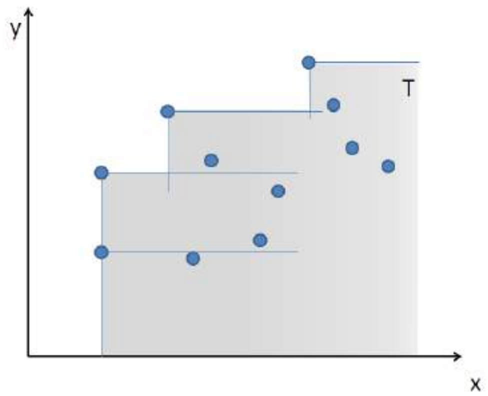

Fig. 6. Free disposable hull

The convexity assumption implies that any linear combination of the feasible production plans (x^k, y^k) is also feasible. The convex VRS technology set is defined in the following way:

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

By combining assumptions of the free disposability, VRS, and convexity (cf. Eqs. 19 and 20) the following technology set is obtained:

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

The latter technology set includes all points that can be considered as feasible ones under assumption of either convexity or free disposability (Figure 7).

DEA is a nonparametric method of measuring the efficiency of a decision–making unit (DMU) such as a firm or a public–sector agency (Ray, 2004).

The modern version of DEA originated in studies of A. Charnes, W. W. Cooper and E. Rhodes (Charnes *et al.*, 1978, 1981). Hence, these DEA models are called CCR models. Initially, the fractional form of DEA was offered. However, this model was transformed into input– and output–oriented multiplier models, which could be solved by means of the linear programming (LP). In addition, the dual CCR model (i. e. envelopment program) can be described for each of the primal programs (Cooper *et al.*, 2007; Ramanathan, 2003).

Unlike many traditional analysis tools, DEA does not require to gather information about prices of materials or produced goods, thus making it suitable for evaluating both private– and public–sector efficiency. Suppose that there are $k = 1,2,\ldots, K$ DMUs, each producing $j = 1,2,\ldots, n$ outputs from $i = 1,2,\ldots, m$ inputs. Hence, the t–th DMU ($t = 1, 2,\ldots, K$) exhibits input–oriented Farrel technical efficiency θ_t, whereas input–oriented Shepard technical efficiency is a reciprocal number and

$\theta_t = 1/\lambda_t$. The input–oriented technical efficiency θ_t may be obtained by solving the following multiplier DEA program:

$$\begin{aligned}
&\min_{\theta_t,\lambda_k} \theta_t \\
&\text{s. t.} \\
&\sum_{k=1}^{K} \lambda_k x_i^k \leq \theta_t x_i^t, \quad i = 1,2,\dots,m; \\
&\sum_{k=1}^{K} \lambda_k y_j^k \geq y_j^t, \quad j = 1,2,\dots,n; \\
&\lambda_k \geq 0, \quad k = 1,2,\dots,K; \\
&\theta_t \text{ unrestricted.}
\end{aligned} \tag{22}$$

Meanwhile, the output–oriented technical efficiency ϕ_t may be obtained by solving the following multiplier DEA program:

$$\begin{aligned}
&\max_{\phi_t,\lambda_k} \phi_t \\
&\text{s. t.} \\
&\sum_{k=1}^{K} \lambda_k x_i^k \leq x_i^t, \quad i = 1,2,\dots,m; \\
&\sum_{k=1}^{K} \lambda_k y_j^k \geq \phi_t y_j^t, \quad j = 1,2,\dots,n; \\
&\lambda_k \geq 0, \quad k = 1,2,\dots,K; \\
&\phi_k \text{ unrestricted.}
\end{aligned} \tag{23}$$

In Eqs. 22 and 23, coefficients λ_k are weights of peer DMUs. Noteworthy, this model presumes existing constant returns to scale (CRS), which is rather arbitrary condition. CRS indicates that the manufacturer is able to scale the inputs and outputs linearly without increasing or decreasing efficiency (Ramanathan, 2003).

Whereas the CRS constraint was considered over–restrictive, the BCC (Banker, Charnes, and Cooper) model was introduced (Banker *et al.*, 1984). The CRS presumption was overridden by introducing a convexity constraint $\sum_{k=1}^{K} \lambda_k = 1$, which enabled to tackle the variable returns to scale (VRS). The BBC model, hence, can be written by supplementing Eqs. 22 and 23 with a convexity constraint $\sum_{k=1}^{K} \lambda_k = 1$.

The best achievable input can therefore be calculated by multiplying actual input by technical efficiency of certain DMU (cf. Eq. 22). On the other hand, the best achievable output is obtained by multiplying the actual output by the output-oriented technical efficiency, where technical efficiency scores are obtained by the virtue of Eq. 23. The difference between the actual output and the potential one is called the radial slack. Let us consider point (x^1, y^1) in Figure 7. We can note that the latter point is projected onto the efficiency frontier by reducing input x^1 to θx^1 (radial movement); however output still needs to be improved by the non-radial movement from y^1 to y^E.

In addition it is possible to ascertain whether a DMU operates under increasing returns to scale (IRS), CRS, or decreasing returns to scale (DRS). CCR measures gross technical efficiency (TE) and hence resembles both TE and scale efficiency (SE); whereas BCC represents pure TE. As a result, pure SE can be obtained by dividing CCR TE by BCC TE. Noteworthy, technical efficiency describes the efficiency in converting inputs to outputs, while scale efficiency recognizes that economy of scale cannot be attained at all scales of production (Ramanathan, 2003).

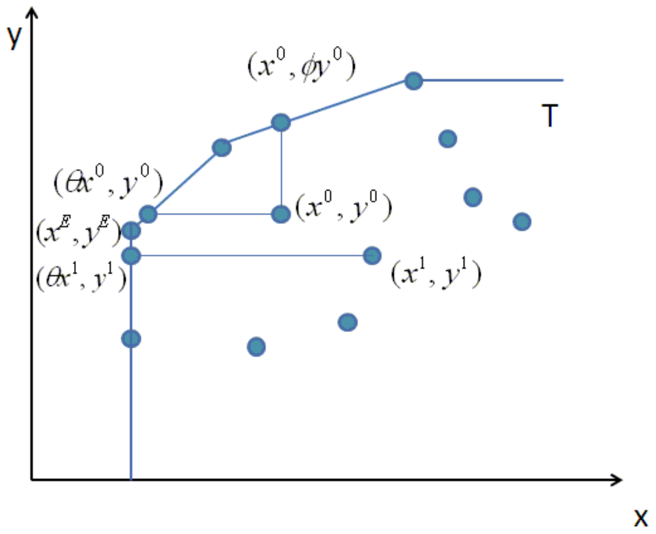

Fig. 7. Data envelopment analysis model

DEA is considered as an axiomatic approach for it satisfies the axioms of convexity, free disposability, and minimal extrapolation (Afriat, 1972). The axiom of minimal extrapolation implies that the observed data are enveloped by a frontier which features the minimal distance between itself and the data. As a result, the underlying production is given as

$$y_t^* = f(x^t) = \max\left\{ y \mid y = \sum_{k=1}^{K} \lambda_k y^k, x^t \geq \sum_{k=1}^{K} \lambda_k x^k, \sum_{k=1}^{K} \lambda_k = 1, \lambda_k \geq 0 \right\}.$$

It is due to Thanassoulis et al. (2008) that the cost efficiency is obtained by the virtue of the following linear cost minimization model:

$$\begin{aligned} &\min_{\lambda_k, x_i} c(y,w) = \sum_{i=1}^{m} w_i^t x_i \\ &\text{s. t.} \\ &\sum_{k=1}^{K} \lambda_k x_i^k \leq x_i, \quad i = 1,2,\ldots,m \\ &\sum_{k=1}^{K} \lambda_k y_j^k \geq y_j^t, \quad j = 1,2,\ldots,n \end{aligned} \tag{24}$$

,

where w_i^t are the input prices for the t–th DMU. Indeed, this model yields the minimum cost which is the input for Eq. 17

Recently, many improvements to DEA have been offered (Shetty, Pakkala, 2010; Zerafat Angiz *et al.*, 2010; Wang *et al.*, 2009) which mainly focus on imposing peer weight restrictions and thus making DEA a more robust instrument for ranking of the DMUs. Moreover, bootstrapping techniques might be employed to estimate confidence intervals for the efficiency scores (Wilson, 2008; Odeck, 2009).

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 base model proposed by Aigner *et al.* (1977) and Meeusen and van den Broeck (1977) then can be presented in the following manner:

$$y^k = f(x^k)TE_k e^{v_k}. \tag{25}$$

The base model after a log transformation becomes

$$\begin{aligned} & y^k = f(x^k, \beta) + v^k - u^k \\ & v^k \sim N(0, \sigma_v^2), u^k \sim N_+(0, \sigma_u^2) \end{aligned}, \tag{26}$$

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: $TE_k = \exp(-u)$.

As one can note, a disturbance term in Eq. 26 consists of an inefficiency measure, *u*, and a random error, *v*, with the former being independently identically distributed truncated normal (half-normal) variable and the latter one being independently identically distributed normal variable. Therefore we cannot use OLS to decompose the disturbance term. The maximum likelihood method[1] is therefore applied.

[1] The method of maximum likelihood (ML) can be applied for the following linear model (Maddala, 2001):

$$y_i = \alpha + \beta x_i + u_i \quad u_i \sim iidN(0, \sigma^2),$$

where y_i are independently and normally distributed with respective means $\alpha + \beta x_i$ and a common variance σ^2. The joint density of the observations, therefore, is $f(y_1, y_2, \dots, y_n) = \prod_{i=1}^{n} \left(\frac{1}{2\pi\sigma^2} \right)^{1/2} \exp\left[-\frac{1}{2\sigma^2}(y_i - \alpha - \beta x_i)^2 \right]$.

In case the parameters *β* are fixed, we have a density function. In case, we have a set of observations and analyse a density function in terms of parameters $(\alpha, \beta, \sigma^2)$ the latter is called a likelihood function and denoted by $L(\alpha, \beta, \sigma^2)$. The essence of the ML method is to choose these parameters so that they maximize this likelihood function. Commonly it is more convenient to maximize the logarithm of the likelihood function:

$$\ln L = \sum_{i=1}^{n} \left(-\frac{1}{2}\ln(2\pi\sigma^2) - \frac{1}{2\sigma^2}(y_i - \alpha - \beta x_i)^2 \right).$$

First, we need the likelihood function describing the SFA model (Eq. 26). The density function for the error term, *v*, of a certain observation is the normal distribution (Bogetoft, Otto, 2011):

$$\varphi_v(v)=\frac{1}{\sqrt{2\pi\sigma_v^2}}\exp\left(-\frac{1}{2}\frac{v^2}{\sigma_v^2}\right), \tag{27}$$

where σ_v^2 is the variance of *v*. The inefficiency term, *u*, follows the half–normal distribution truncated at zero:

$$\varphi_u(u)=\begin{cases}\frac{2}{\sqrt{2\pi\sigma_u^2}}\exp\left(-\frac{1}{2}\frac{u^2}{\sigma_u^2}\right) & \text{for } u\geq 0\\ 0 & \text{for } u<0\end{cases}, \tag{28}$$

here the extra 2-factor is introduced to maintain the total mass of the half-normal distribution equal to unity, i. e. $\int_{-\infty}^{+\infty}\varphi_u(u)du=1$.

Having a set of observations (x,y), one cannot directly calculate the *v* and *u* terms. Indeed, it is possible to calculate the total error term $\varepsilon=v-u=y-f(x,\beta)$. The distribution of ε, thus, is the convolution of distributions of *v* and −*u*:

$$\varphi_\varepsilon(\varepsilon)=\int_{-\infty}^{+\infty}\varphi_u(u)\varphi_v(\varepsilon+u)du=\int_0^{+\infty}\varphi_u(u)\varphi_v(\varepsilon+u)du. \tag{29}$$

After setting

$$\sigma^2=\sigma_v^2+\sigma_u^2, \tag{30}$$

$$\lambda=\sqrt{\sigma_u^2/\sigma_v^2}, \tag{31}$$

and combining Eqs. 27–29 we get

$$\varphi_\varepsilon(\varepsilon)=\frac{\sqrt{2}}{\sqrt{\pi\sigma^2}}\Phi\left(-\frac{\lambda\varepsilon}{\sqrt{\sigma^2}}\right)\exp\left(-\frac{1}{2}\frac{\varepsilon^2}{\sigma^2}\right), \tag{32}$$

with $\Phi(\cdot)$ being the distribution function of the standard normal distribution with zero mean, and variance of unity, i. e. $\Phi(z)=\frac{1}{\sqrt{2\pi}}\int_{-\infty}^{z}e^{-\frac{1}{2}t^2}dt$. When the parameter *λ* is 0, there is no effect from differences in efficiency and when it gets larger, the larger part of the whole disturbance term is attributed to variation in efficiency. The logged density function gets the following form:

$$\ln\varphi_\varepsilon(\varepsilon)=-\frac{1}{2}\ln\left(\frac{\pi}{2}\right)-\frac{1}{2}\ln\sigma^2+\ln\Phi\left(-\frac{\lambda\varepsilon}{\sqrt{\sigma^2}}\right)-\frac{1}{2}\frac{\varepsilon^2}{\sigma^2}. \tag{33}$$

In case we have *K* observations, the joint density function becomes

$$\varphi(\varepsilon_1,\varepsilon_2,\ldots,\varepsilon_K)=\prod_{k=1}^{K}\varphi_\varepsilon(\varepsilon_k), \tag{34}$$

and the logarithm of the joint density function is then given by

$$\begin{aligned}\ln \varphi(\varepsilon_1, \varepsilon_2, ..., \varepsilon_K) &= \sum_{k=1}^{K} \varphi_\varepsilon(\varepsilon_k) \\ &= -\frac{K}{2}\ln\left(\frac{\pi}{2}\right) - \frac{K}{2}\ln\sigma^2 + \sum_{k=1}^{K}\ln\Phi\left(-\frac{\lambda\varepsilon_k}{\sqrt{\sigma^2}}\right) - \frac{1}{2\sigma^2}\sum_{k=1}^{K}\varepsilon_k^2\end{aligned} \quad (35)$$

By taking into account that the error term ε_k depends on the vector of parameters, β, we can rearrange Eq. 35 into the following log likelihood function:

$$\begin{aligned}l(\beta, \sigma^2, \lambda) &= \ln \varphi_e(\varepsilon_1(\beta), \varepsilon_2(\beta), ..., \varepsilon_K(\beta); \sigma^2, \lambda) \\ &= \ln \varphi_e(y_1 - f(x_1, \beta), y_2 - f(x_2, \beta), ..., y_K - f(x_K, \beta); \sigma^2, \lambda) \\ &= -\frac{K}{2}\ln\left(\frac{\pi}{2}\right) - \frac{K}{2}\ln\sigma^2 + \sum_{k=1}^{K}\ln\Phi\left(-\frac{\lambda(y_k - f(x_k, \beta))}{\sqrt{\sigma^2}}\right) - \frac{1}{2\sigma^2}\sum_{k=1}^{K}(y_k - f(x_k, \beta))^2\end{aligned} \quad (36)$$

The function $l(\beta, \sigma^2, \lambda)$ is the log-likelihood function which depends on the parameters β, σ^2, λ and on the observed data $(x_1, y_1), ..., (x_K, y_K)$. Thus, the maximum of the log-likelihood function is found by equating every element of its gradient to zero. The existing non-linearity, however, does not allow achieving a closed-form solution. Therefore, an iterative optimization algorithm, namely Newton's method, is employed to estimate the parameters.

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:

$$\ln y_k = \ln \beta_0 + \sum_{i=1}^{m} \beta_i \ln x_i^k + v^k - u^k \quad (37)$$

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

$$\ln y_k = \beta_0 + \sum_{i=1}^{m} \beta_i \ln x_i^k + \frac{1}{2}\sum_{i=1}^{m}\sum_{l=1}^{m} \beta_{il} \ln x_i^k \ln x_l^k + v^k - u^k. \quad (38)$$

As one can note, production functions defined by Eqs. 37–38 can tackle 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:

$$D_I^k(x^k, y^k) = x_m^k D_I^k\left(\frac{x^k}{x_m^k}, y^k\right), \quad (39)$$

$$D_O^k(x^k, y^k) = y_n^k D_O^k\left(x^k, \frac{y^k}{y_n^k}\right). \quad (40)$$

By logging both sides of Eqs. 39–40 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:

$$\ln\left(\frac{1}{x_m^k}\right) = \ln D_I^k\left(\frac{x^k}{x_m^k}, y^k\right) - u^k, \tag{41}$$

$$\ln\left(\frac{1}{y_n^k}\right) = \ln D_O^k\left(x^k, \frac{y^k}{y_n^k}\right) - u^k. \tag{42}$$

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:

$$\ln\left(\frac{1}{x_m^k}\right) = a_0 + \sum_{i=1}^{m-1} a_i \ln\frac{x_i^k}{x_m^k} + \sum_{j=1}^{n} b_j \ln y_j^k + \frac{1}{2}\sum_{i=1}^{m-1}\sum_{l=1}^{m-1} \alpha_{il} \ln\frac{x_i^k}{x_m^k}\ln\frac{x_l^k}{x_m^k} + \frac{1}{2}\sum_{j=1}^{n}\sum_{p=1}^{n} \beta_{jp} \ln y_j^k \ln y_p^k + \frac{1}{2}\sum_{i=1}^{m-1}\sum_{j=1}^{n} \gamma_{ij} \ln\frac{x_i^k}{x_m^k}\ln y_j^k + v^k - u^k. \tag{43}$$

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

$$\ln\left(\frac{1}{y_n^k}\right) = a_0 + \sum_{i=1}^{m} a_i \ln x_i^k + \sum_{j=1}^{n-1} b_j \ln\frac{y_j^k}{y_n^k} + \frac{1}{2}\sum_{i=1}^{m}\sum_{l=1}^{m} \alpha_{il} \ln x_i^k \ln x_l^k + \frac{1}{2}\sum_{j=1}^{n-1}\sum_{p=1}^{n-1} \beta_{jp} \ln\frac{y_j^k}{y_n^k}\ln\frac{y_p^k}{y_n^k} + \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n-1} \gamma_{ij} \ln x_i^k \ln\frac{y_j^k}{y_n^k} + v^k - u^k. \tag{44}$$

Equations 43 and 44 imply that we only need to estimate $a_1, a_2, \ldots, a_{m-1}$ and $b_1, b_2, \ldots, b_{n-1}$, 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 translog cost function. After imposing its homogeneity it has the following form:

$$\ln\frac{C_k}{w_m} = \alpha_0 + \sum_{i=1}^{m-1} \alpha_i \ln\frac{w_i^k}{w_m^k} + \sum_{j=1}^{n} \beta_j \ln y_j^k + \frac{1}{2}\sum_{i=1}^{m-1}\sum_{l=1}^{m-1} \gamma_{il} \ln\frac{w_i^k}{w_m^k}\ln\frac{w_l^k}{w_m^k} + \frac{1}{2}\sum_{j=1}^{n}\sum_{p=1}^{n} \delta_{jp} \ln y_j^k \ln y_p^k + \frac{1}{2}\sum_{i=1}^{m-1}\sum_{j=1}^{n} \phi_{ij} \ln\frac{w_i^k}{w_m^k}\ln y_j^k + v^k + u^k, \tag{45}$$

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. Note that inefficiency term, u^k, increases the value of cost function. Accordingly, special treatment of these functions are needed when employing statistical packages (e. g. package *frontier* in *R*).

3. STATE-OF-THE-ART OF THE AGRICULTURAL EFFICIENCY RESEARCH

This section presents a literature survey on efficiency analyses in agriculture. The first sub-section tackles the foreign literature, whereas the second one focuses on the Lithuanian researches.

3. 1. Foreign literature survey

As Henningsen (2009) put it, the agricultural efficiency is interrelated with labour intensity, farm structure, technology and investment, managerial skills, and profitability. The very efficiency thus can be considered as a measure of productivity and profitability. The farm structure impacts technology, labour intensity, and managerial skills given larger farms tend to accumulate respective resources to a higher extent. The labour intensity and labour opportunity costs are reciprocally related to the investments into advanced technologies. Management skills also influence both labour intensity and investments into technology. The aforementioned factors affect the profitability, whereas the profitability, in turn, determines farmers' decisions on staying in the sector or distributing their working time across various economic sectors. The productive efficiency, therefore, needs to be measured and analyzed in terms of multiple interrelated variables and dimensions. Furthermore, the 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 and Boone (2009) benchmarking can create motivation for change; provide a vision for what an organization can look like after change; provide data, evidence, and success stories for inspiring change; identify best practices for how to manage change; and create a baseline or yardstick by which to evaluate the impact of earlier changes.

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 and Latruffe, 2011).

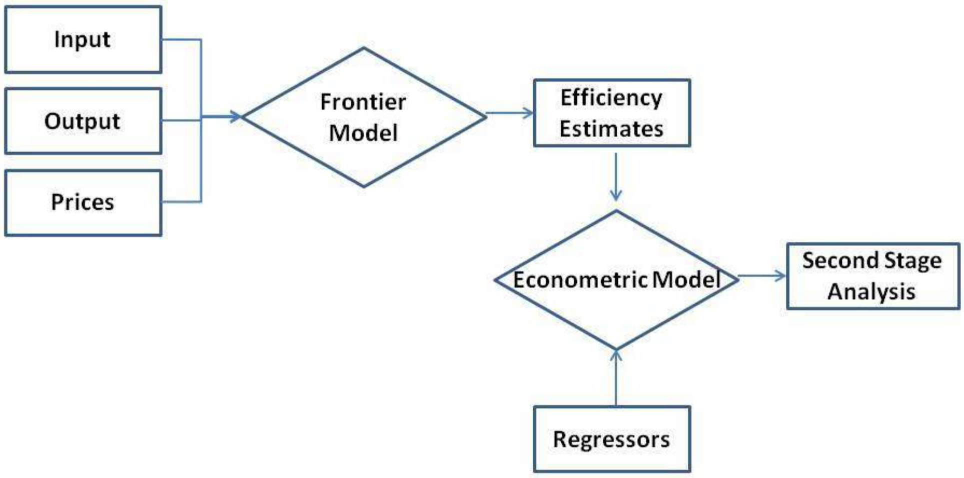

Fig. 8. The conceptual framework for the frontier-based benchmarking

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 analyze 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 analyzed 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.

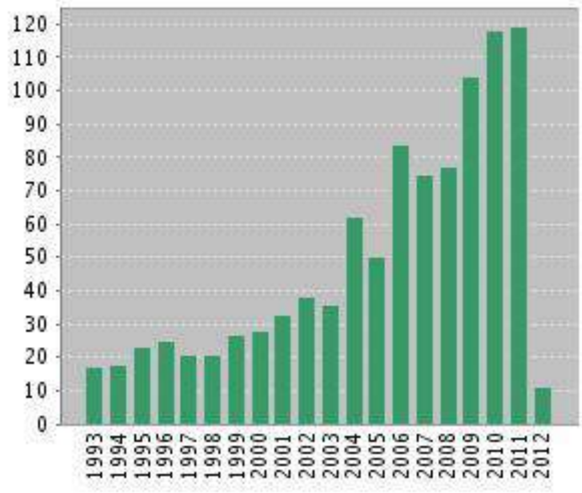

Fig. 9. Published items in each year

Source: Thomson Reuters.

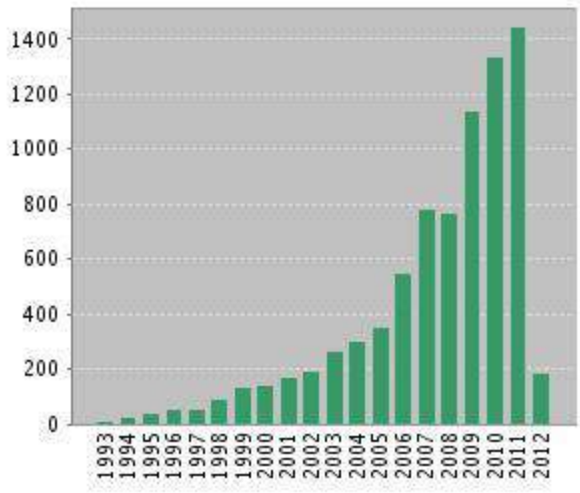

Fig. 10. Citations in each year

Source: Thomson Reuters.

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.

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

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.

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) analyzed 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) as a land factor, annual work units (AWU) as a labour factor, depreciation plus interests as a capital factor, and intermediate consumption as a variable factor. The following variables were chosen as the determinants 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 and Latruffe (2008) analyzed 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 analyzed farming types into relatively homogeneous groups, however there was no second state analysis performed. Later on, efficiency was related to the farm structure (Bojnec, Latruffe, 2011). 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 analyze beef cow/calf farming in Canada. Lambarraa and 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 and 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).

A meta-regression analysis[2] including 167 farm level technical efficiency studies of developing and developed countries was undertaken by Bravo-Ureta *et al.* (2006). The econometric results suggested that stochastic frontier models generate lower mean TE estimates than non-parametric deterministic models, while parametric deterministic frontier models yield lower estimates than the stochastic approach. The primal approach had been the most common technological representation. In addition, frontier models based on cross-sectional data had produced lower estimates than those based on panel data whereas the relationship between functional form and mean TE is inconclusive. On average, studies for animal production had shown a higher mean TE than crop farming. The results also suggest that the studies for countries in Western Europe and Oceania present, on average, the highest levels of mean TE among all regions after accounting for various methodological features.

3. 2. Lithuanian literature survey

Productive efficiency of agricultural sector is extensively analyzed across the Central and East European states where agriculture is relatively important economic activity if compared to the western states (Gorton and Davidova, 2004). The Lithuanian agricultural sector, though, received less attention in the latter scientific area. Moreover, those few examples employed non-parametric methods, whereas parametric methods (e. g. stochastic frontier analysis) remain underused. The remaining part of this section overviews earlier papers which analysed efficiency of the Lithuanian agricultural sector by the means of frontier measures, namely DEA.

The paper by Rimkuvienė *et al.* (2010) also addressed the farming efficiency by performing an international comparison on a basis of DEA and free disposal hull—the two non-parametric methods. This study also discussed the differences between terms efficiency and effectiveness which are often misused in Lithuanian scientific works. The research covered years 2004–2008 and some 174 observations (aggregates) for EU and non-EU states. Input- and output-oriented DEA models yielded efficiency scores of 43.2 and 41.4%, respectively. In addition the effectiveness of capital and intermediate consumption was observed in Lithuania.

Baležentis and Baležentis (2011) followed the similar framework for international comparison. However, the latter study employed not only DEA but also multi-criteria decision making method MULTIMOORA. The agricultural efficiency was assessed with respect to the three ratios, namely crop output (EUR) per ha, livestock output (EUR) per LSU, and farm net value added (EUR) per AWU. Therefore, the land, livestock, and labour productivity were estimated. According to the DEA efficiency

[2] Meta-regression analysis is based on results of the previous (econometric) researches. In this particular case the obtained mean efficiency scores were related to certain variables describing the environment of respective farming systems.

scores, Lithuania and Latvia reached the efficiency of 52 and 54%, whereas Estonia and Poland that of 58%. The high value of slacks in crop output (land productivity) and the net value added per AWU (labour productivity) for the three Baltic States indicated the necessity of qualitative and quantitative changes to be implemented here.

It was Douarin and Latruffe (2011) who offered the single foreign contribution to the DEA-based efficiency analysis of Lithuanian agriculture. The aim of that study was to estimate the farming efficiency and possible outcomes of the incentives provided by EU Single Area Payments. Moreover, this study was based on micro- rather than aggregate data. Thus, farm efficiency estimation was followed by questionnaire survey which tried to identify the farmers' behaviour, namely decisions to expand their farms or stay in the farming sector, as a result of public support distribution. The research showed that 1) larger farms operated more efficiently, 2) subsidies were related to lower efficiency scores. The Heckman model was employed to quantify the impact of various factors on farmers' decisions to stay in farming or expand the farm. It was concluded that the overall farming efficiency should decrease, for lower efficiency farms were about to expand and thus increase competition in the land market.

Baležentis and Kriščiukaitienė (2012) also analyzed performance of the Lithuanian family farms on a basis of FADN aggregates. The DEA was employed for the analysis. As a result, slack analysis revealed that low land productivity, returns on assets, and intermediate consumption productivity are the most important sources of the inefficiency, in that order. Low land productivity is especially important for specialised cereals and general field cropping. Therefore, the incentives for crop structure adjustment should be imposed in order to increase land productivity. The highest mean values of return on assets slacks were observed for specialist cereal farming and general field cropping.

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.

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

4. EMPIRICAL ANALYSIS

This section presents the data used as well as the results of the research. The research involved DEA and SFA as the estimators of the efficiency scores, therefore the section is structured accordingly.

4. 1. Data used

The technical and scale efficiency was assessed in terms of the input and output indicators commonly employed for agricultural productivity analyses (Bojnec, Latruffe 2008, 2011; Douarin, Latruffe 2011). More specifically, the utilized agricultural area (UAA) in hectares was chosen as land input variable, annual work units (AWU) – as labour input variable, intermediate consumption in Litas was used as a variable of the variable costs, and total assets in Litas as a capital factor. On the other hand, the three output indicators represent crop, livestock, and other outputs in Litas, respectively. Indeed, the three output indicators enable to tackle the heterogeneity of production technology across different farms.

The cost efficiency was estimated by defining respective prices for each of the four inputs described earlier. The land price was obtained from the Eurostat and assumed to be uniform for all farms during the same period. The labour price is the average salary in agricultural sector from Statistics Lithuania. The price of capital is depreciation plus interests per one Litas of assets. Meanwhile, the intermediate consumption is directly considered as a part of total costs.

The data for 200 farms selected from the FADN sample cover the period of 2004–2009. Thus a balanced panel of 1200 observations is employed for analysis. The analyzed sample covers relatively large farms (mean UAA – 244 ha). As for labour force, the average was 3.6 AWU.

In order to quantify the factors influencing the agricultural productivity, we employed the following indicators for the second–stage analysis. Total output was used to identify relationship between farm size and efficiency. Soil index was used to check whether it significantly influences productivity. Farmer's age was used to test the linkage between demographic processes and efficiency. The dummy variable for organic farming was introduced to explore the performance of the organic farms. The share of crop output in the total output was used to ascertain whether either the crop or livestock farming is more efficient in Lithuania. The ratio of production subsidies to the total output was employed to estimate the effect of support payments, whereas the ratio of subsidies for equipment to the total output was defined to identify the impact of capital investments.

4. 2. Non-parametric analysis of the productive efficiency

The non-parametric method, DEA, was employed to estimate the efficiency scores. The DEA-based efficiency scores were then analysed by the means of the tobit and logit models. This sub-section presents the results of the analysis.

4. 2. 1. Dynamics of the efficiency scores

The input–oriented VRS DEA model (Eq. 22) was employed to analyze the FADN data which were arranged into the cross–section table. The cost efficiency estimates were obtained by employing Eq. 24. The summary of efficiency scores is presented in Table 2. The latter table describes the mean values for the whole period of 2004–2009.

Considering the VRS technology, the mean technical efficiency fluctuated around 65.8%, which virtually means that average farm should reduce its inputs by some 35% and sustain the same output level to achieve the efficiency frontier (these numbers do also include the scale effect). The mean value of allocative efficiency was equal to 70.5% and indicated that the cost productivity can be increased by 29.5% due to changes in input–mix. Considering these types of efficiency, the mean economic efficiency—or, alternatively, cost efficiency—of 46% was observed for the Lithuanian family farms. Therefore, these farms should be able to produce the same amount of output given the input vector is scaled down by some 54%. Suchlike shifts, however, might not be feasible for every farm given they are specific with certain heterogeneity across farming types. Table 2 also suggests that the highest variation was observed for the economic efficiency estimates where coefficient of variation was 7.2% for VRS technology.

Table 2. Descriptive statistics of input–oriented technical (TE), scale (SE), allocative (AE), and cost (CE) efficiency scores under CRS and VRS assumptions

	TE		SE	AE		CE	
	VRS	CRS		VRS	CRS	VRS	CRS
Arithmetic Mean	0.658	0.535	0.834	0.705	0.747	0.460	0.401
Median	0.628	0.520	0.925	0.728	0.758	0.436	0.376
Standard Deviation	0.204	0.193	0.205	0.167	0.118	0.182	0.166
Sample Variance	0.042	0.037	0.042	0.028	0.014	0.033	0.027
Coefficient of variation	0.063	0.070	0.051	0.040	0.019	0.072	0.068
Minimum	0.154	0.070	0.093	0.105	0.293	0.099	0.037
Maximum	1	1	1	1	1	1	1

The intensity variables (peer weights) involved in Eq. 22 defines the shape of the production frontier. These variables, therefore, enable to assess whether the DMU is operating in the range of increasing, constant, or decreasing returns to scale. In case the DMU is operating in the range of DRS (IRS) returns to scale, it is said to be operating at the supra-optimal (sub-optimal) scale. Grosskopf (1986) offered a methodology to determine the range of scale returns the DMU operates in. for this purpose one needs to estimate efficiency scores under non-increasing returns to scale (NIRS). The said estimates can be obtained by supplementing Eq. 22 with the following convexity constraint: $\sum_{k=1}^{K}\lambda_k = 1$. For the input-oriented DEA, the following rules hold: If $\theta^{CRS} = \theta^{VRS}$, then the DMU operates under CRS (i. e. at the optimal scale). If $\theta^{CRS} < \theta^{NIRS} = \theta^{VRS}$, the DMU operates under DRS. If $\theta^{CRS} = \theta^{NIRS} < \theta^{VRS}$, the DMU operates under IRS.

The following Fig. 11 presents the dynamics of the farm structure in terms of returns to scale. As one can note the share of farms experiencing increasing returns to scale fluctuated in between the minimum value of 81% in 2008 and the maximum value of 95% in 2006. Hence, the largest share of the observed farms was operating at a sub–optimal scale and could increase its efficiency by increasing the operation scale. Meanwhile the share of farms operating at the optimal scale was close to nil and oscillated in between 0.5% and 8%.

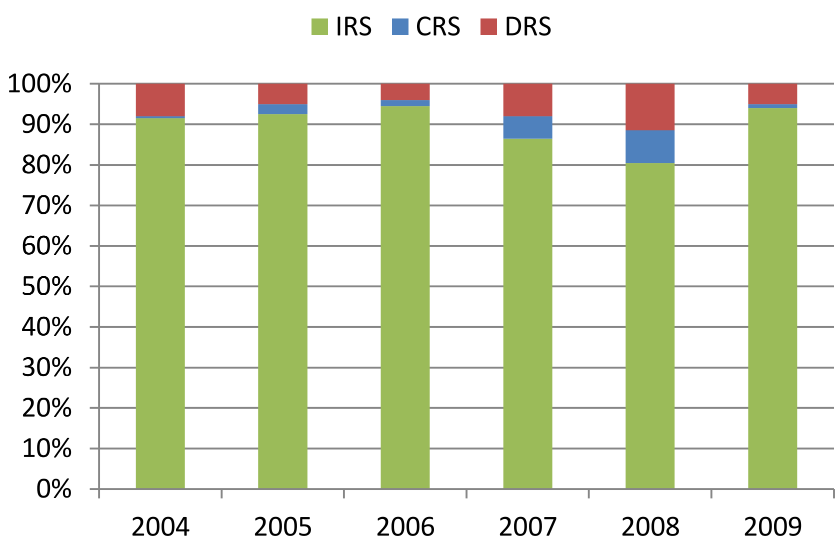

Fig. 11. The share of farms experiencing decreasing (DRS), constant (CRS), and increasing (IRS) returns to scale, 2004–2009

The dynamics of different types of efficiency throughout 2004–2009 is presented in Table 3. As one can note, there were two major shocks in productive efficiency: the first one occurred in 2006, whereas the second one – in 2009. Obviously the former is related to worsened climatic conditions, for the mean grain yield dropped from 28.9

t/ha in 2005 down to 18.8 t/ha in 2006 (Statistics Lithuania, 2011). The second shock is related to some turmoil in the agricultural markets.

Considering the variation of different types of efficiency one can conclude that the cost efficiency (CE) was the most time–variant, whereas the allocative efficiency (AE) – the most time–invariant. Indeed, the coefficients of variation presented in Table 2 are 4% for AE and 7.2% for CE under VRS. Therefore, the shifts in economic efficiency can be attributed to shifts in technical and scale efficiency to a higher extent. This finding indicates that farmers tend to adjust the input–mix for their farms at a reasonable rate given the changes in prices of the production factors.

Table 3. Dynamics of the Lithuanian family farm efficiency (DEA estimates), 2004–2009

	TE		SE	AE		CE	
	VRS	CRS		VRS	CRS	VRS	CRS
Crop farming							
2004	0.69	0.52	0.79	0.66	0.77	0.46	0.40
2005	0.61	0.47	0.80	0.64	0.73	0.39	0.34
2006	0.53	0.38	0.76	0.57	0.71	0.31	0.27
2007	0.69	0.63	0.91	0.72	0.75	0.50	0.47
2008	0.68	0.62	0.91	0.72	0.75	0.49	0.46
2009	0.57	0.46	0.84	0.65	0.75	0.37	0.34
Average	0.63	0.51	0.84	0.67	0.75	0.42	0.38
Livestock farming							
2004	0.74	0.67	0.91	0.85	0.83	0.63	0.56
2005	0.84	0.75	0.89	0.83	0.83	0.70	0.62
2006	0.77	0.67	0.87	0.79	0.78	0.60	0.52
2007	0.87	0.81	0.93	0.82	0.80	0.72	0.65
2008	0.85	0.80	0.94	0.81	0.79	0.69	0.63
2009	0.70	0.63	0.89	0.81	0.83	0.57	0.52
Average	0.80	0.72	0.90	0.82	0.81	0.65	0.58
Mixed farming							
2004	0.78	0.50	0.67	0.78	0.75	0.61	0.38
2005	0.71	0.53	0.77	0.73	0.70	0.52	0.37
2006	0.66	0.44	0.71	0.70	0.66	0.46	0.29
2007	0.72	0.59	0.82	0.78	0.75	0.56	0.44
2008	0.72	0.56	0.79	0.74	0.69	0.54	0.39
2009	0.61	0.44	0.75	0.74	0.72	0.45	0.32
Average	0.70	0.51	0.75	0.74	0.71	0.52	0.36

Note: the reported estimates are the input–oriented technical (TE), scale (SE), allocative (AE), and cost (CE) efficiency scores under CRS and VRS assumptions

Although the discussed descriptives of the efficiency scores provide some insights, the further analysis is needed to fathom the processes affecting productive efficiency. The underlying causes and sources of inefficiency thus are further analyzed by the means of tobit and logit models.

4. 2. 2. Explaining inefficiency: tobit and logit models

This section explores the main determinants of inefficiency and quantifies their impact on efficiency scores or dynamics thereof. We have defined the two main foci for our post–efficiency analysis, namely (i) tobit regression for particular factors of efficiency and (ii) logit regression for factors influencing longitudinal changes in efficiency.

The following factors were chosen as regressors. The logged output (*lnOutput*) identified the scale of operation and was considered a proxy for farm size. Indeed, the question of the optimal farm size has always been a salient issue for policy makers and scientists (Alvarez, Arias, 2004; Gorton, Davidova, 2004; van Zyl et al., 1996). The soil quality index (*Soil*) was included in the models to test the relationship between the environmental conditions and efficiency. The ratio of crop output to the total output (*CropShare*) captures the possible difference in farming efficiency across crop and livestock farms. Similarly, the dummy variable for organic farms (*Organic*) was used to quantify the difference between organic and conventional farming. It is due to Offermann (2003) that Lithuanian organic farms exhibit 60–80% lower crop yields depending on crop species if compared to same values for conventional farming. The demographic variable, namely age of farmer (*Age*) was introduced to ascertain whether young farmers–oriented measures can influence the structural efficiency. Finally, the effect of production and equipment subsidies on efficiency was estimated by considering ratios of production subsidies to output (*SubsShare*) and equipment subsidies to output (*ESubsShare*), respectively.

4. 2. 2. 1. Tobit model

Given the efficiency scores are bounded to the interval [0, 1], one needs to use the tobit model for the second stage analysis (Bogetoft, Otto, 2011; Samarajeewa et al., 2012). An implicit assumption of the tobit approach is that an unobservable latent variable E^* underlies the observed sample (Hoff, Vestergaard, 2003). A linear model describes the relationship between E^* and explanatory variables x_i: $E_k^* = \sum_i \beta_i x_{ki} + u_k = \beta x_k + u_k$, where u_k is the error term. Due to censoring of the dependent variable (viz. efficiency score) one observes the bounded variable E which gets the following values:

$$E_k = \begin{cases} a, \beta x_k + u_k \le a \\ \beta x_k + u_k, a < \beta x_k + u_k < b \\ b, b \le \beta x_k + u_k \end{cases}, \quad (46)$$

where a and b are the lower and upper bounds of the censored variable, respectively. Maximum likelihood function is therefore defined to fit the model for the sample data; see Bogetoft and Otto (2011) as well as Hoff and Vestergaard (2003) for further details.

As for DEA efficiency scores, we can always bound them to the interval [0, 1]. Indeed usually neither of the DMUs exhibit zero–valued efficiency. The lower bound a thus can be dropped from Eq. 46.

Given the abovementioned peculiarities of the tobit model, the marginal effect of a single explanatory variable x_i is a function of the whole vector of coefficients β, explanatory variables themselves, variance of the error term σ, and bounds a and b:

$$\frac{\partial EV(E\mid x)}{\partial x_i}=\beta_i\left(\Phi\left(\frac{b-\beta x_k}{\sigma}\right)-\Phi\left(\frac{a-\beta x_k}{\sigma}\right)\right), \tag{47}$$

where Φ is the standard normal density function.

The three tobit models were specified for cost (economic), allocative, and technical efficiency with previously defined factors as regressors. Tables 4 and 5 present the fitted tobit model.

As one can note, the autoregressive terms were included in the three tobit models (Table 4) to increase their robustness. The backward procedure was carried out in terms of heteroskedasticity and autocorrelation consistent (HAC) z values. Therefore, Tables 4 and 5 present the significant factors of efficiency. Specifically, Eq. 47 was employed to estimate marginal effects in Table 5.

The tobit regression (cf. Table 4) suggests that both cost and allocative efficiency is positively impacted by the scale of operation (i. e. the amount of output), whereas technical efficiency has no significant relation to the latter variable. Therefore it can be concluded that the larger farms are more likely to make more efficient decisions regarding input–mix. Indeed bigger quantities involved in supply and production chain management in larger farms provide more flexibility for large farms. This is especially the case in rather small market of Lithuania. Although some other studies reported efficiency to follow U-shaped curve across farm size groups (Latruffe et al. 2004), our findings might diverge from the forms, given we analyze sample particularly covering large farms. Thus only the right tail of the efficiency curve is what we focus at.

The soil index had a negative impact on the three types of efficiency, namely cost, allocative, and technical efficiency. Furthermore, these effects are for the whole range of the values of the latter indicator (Table 5). Soil quality, hence, affects both technology and input management. This finding is likely to be an outcome of poor estimation methodology for this variable and farming practices related to areas specific with higher soil quality. Indeed, farms located in fertile areas tend to exploit extensive agriculture rather than intensive one and thus opt for less innovative technologies. Further research, however should be conducted to identify the exact factors of the negative link between soil quality index and efficiency.

Table 4. The tobit regression describing the impact of efficiency factors

	CE_t			AE_t			TE_t		
	Estimate	**z value**		**Estimate**	**z value**		**Estimate**	**z value**	
(Intercept)	-0.06957	-1.1875		-0.18017	-3.6132	***	0.334628	5.4576	***
CE_{t-1}	0.669982	16.4166	***						
CE_{t-2}	0.097827	3.0289	**						
AE_{t-1}				0.609962	17.4355	***			
AE_{t-2}				0.1978	5.9876	***			
TE_{t-1}							0.550301	11.9596	***
TE_{t-2}							0.140399	3.1882	**
$lnOutput_t$	0.227834	14.7219	***	0.113541	10.3271	***			
$lnOutput_{t-1}$	-0.2121	-12.0894	***	-0.08851	-7.7249	***			
$Soil_t$	-0.00137	-2.4569	*	-0.00127	-2.4235	*	-0.00226	-2.3506	*
Age_t	0.001312	3.1348	**	0.001025	2.7208	**			
$Organic_t$	0.046929	1.6524	.				0.082167	2.403	*
$CropShare_t$	-0.04764	-2.6511	**						
$SubsShare_t$							-0.10502	-2.945	**
$SubsShare_{t-1}$	-0.05573	-2.8811	**						
Log(scale)	-2.32891	-41.2717	***	-2.27569	-61.3961	***	-1.72798	-49.7414	***

Notes:
(i) CE, AE, and TE stand for cost, allocative, and technical efficiency, respectively;
(ii) z values are heteroskedasticity and autocorrelation consistent (HAC) ones;
(iii) significance codes for respective p values: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1.

Table 5. The marginal efficiency effects for the tobit model

	CE_t				AE_t				TE_t			
	Mean effect	Effect at minimum	Effect at mean	Effect at maximum	Mean effect	Effect at minimum	Effect at mean	Effect at maximum	Mean effect	Effect at minimum	Effect at mean	Effect at maximum
CE_{t-1}	0.662	0.098	0.670	0.349								
CE_{t-2}	0.092	-0.474	0.098	0.051								
AE_{t-1}					0.590	0.042	0.609	0.317				
AE_{t-2}					0.191	-0.370	0.197	0.103				
TE_{t-1}									0.516	0.007	0.541	0.282
TE_{t-2}									0.131	-0.403	0.138	0.072
$lnOutput_t$	0.221	-0.344	0.228	0.119	0.110	-0.455	0.113	0.059				
$lnOutput_{t-1}$	-0.217	-0.784	-0.212	-0.110	-0.086	-0.657	-0.088	-0.046				
$Soil_t$	-0.007	-0.573	-0.001	-0.001	-0.001	-0.569	-0.001	-0.001	-0.003	-0.546	-0.002	-0.001
Age_t	-0.004	-0.571	0.001	0.001	0.001	-0.567	0.001	0.001				
$Organic_t$	0.041	-0.525	0.047	0.024					0.076	-0.461	0.081	0.042
$CropShare_t$	-0.053	-0.620	-0.048	-0.025								
$SubsShare_t$									-0.100	-0.648	-0.103	-0.054
$SubsShare_{t-1}$	-0.061	-0.628	-0.056	-0.029								

Farmer's age had a positive effect on allocative and economic efficiency, albeit this effect was negative for the youngest farmers (Table 5). Thus farmer's age matters to a higher extent for younger farmers, whereas its impact decreases later on. Furthermore, farmer's age is likely to be related to economic rather than technical side of farming.

Organic farming appeared to be more efficient if compared to conventional farming. To be specific, an average organic farm exhibited cost efficiency score which was greater by a margin of 4.7%, whereas technical efficiency increased by some 8.2%. Therefore the results support Tzouvelekas et al. (2001) who argued that organic farming regulations may encourage a more reasonable application of fertilizers etc., which, in turn, determines respective technological improvements. In addition, organic farms produce more expensive production.

Due to the negative coefficient for crop output share in the total output, crop farming can be considered less efficient if compared to animal farming. Indeed, increase in crop share of 1 pp causes decline in efficiency of 4.8% (Table 4), whereas the marginal effect at the maximum crop share diminishes to 2.5% (Table 5). This finding is consistent with study by Latruffe et al. (2004) who discovered similar pattern for Polish farms.

The tobit model suggests that production subsidies had a negative simultaneous effect on technical efficiency, i. e. increase of subsidies to output ratio by 1 p. p. lead to an average decrease in efficiency equal to 10%. Meanwhile, the lagged effect of production subsides on cost efficiency was also observed. Thus production subsidies affected technical efficiency rather than allocative efficiency. As for equipment subsidies, they apparently had no significant effect on level of productive efficiency. The discussed factors determined the level of cost, allocative, and technical efficiency. The following sub–section discusses the impact of those factors on changes in efficiency.

4. 2. 2. 2. Logit model

The logit model is employed to estimate the following regression:

$$y_k^* = \beta_0 + \sum_i \beta_i x_{ki} + u_k , \tag{48}$$

where y_k^* is a latent variable (Maddala, 2001). The observed dummy variable, y_k, gets the binary values:

$$y_k = \begin{cases} 1, y_k^* > 0 \\ 0, \text{ otherwise} \end{cases} . \tag{49}$$

By noting $P_k = Prob(y_k = 1)$ and assuming that u_k is symmetrically distributed, we have

$$P_k = F\left(\beta_0 + \sum_i \beta_i x_{ki}\right), \tag{50}$$

where F is a certain function chosen with respect to the assumed distribution of the error term. In case of the logistic cumulative distribution we have

$$F(Z_k) = \frac{exp(Z_k)}{1 + exp(Z_k)}, \tag{51}$$

and thus

$$\ln \frac{F(Z_k)}{1 - F(Z_k)} = Z_k. \tag{52}$$

As for the logit model, the following equation holds:

$$\ln \frac{P_k}{1 - P_k} = \beta_0 + \sum_i \beta_i x_{ki}, \tag{53}$$

where left-hand side of the equation is called the log-odds ratio and means the ratio between probabilities to observe $y_k = 1$ and $y_k = 0$.

The changes in efficiency scores were explored by the means of logit regression. Therefore we defined $y_k = 1$ in case a certain farm experienced increase in efficiency and $y_k = 0$ otherwise. The same factors as for tobit regression were employed. The backward procedure was carried out with respect to HAC z values. Table 6 presents the final results.

As Table 6 suggests, the larger farms were more likely to experience increase in efficiency. Specifically, the increase in the total output of 1% caused increase of the odd ratio ranging between 1.4 for cost efficiency and 1.6 for technical efficiency. These numbers subsequently are translated into ratio between probabilities of events $y_k = 1$ (i. e. increase in efficiency) and $y_k = 0$, respectively.

The soil quality index exhibited a negative relation to increase in economic, allocative, and technical efficiency. These relationships can be explained by insufficient pressure for farmers who have their farms located in fertile areas to adopt innovative managerial practices.

Crop farming is more likely to achieve positive shift in allocative efficiency (effect on odd ratio accounts 1.6 times), though it is not the case for cost and technical efficiency. Indeed, crop market is rather dynamic and therefore farmers can adjust their decisions related to input–mix in a more dynamic way.

The fitted logit model imposes that farms adopted organic farming increase their odd ratio for achieving higher cost efficiency at a margin of 8.2, whereas gains in technical efficiency are also to be positively affected by the same decision.

Table 6. Coefficients of the logit regression describing shifts in efficiency scores with respect to certain determinants of efficiency

	CE_t			AE_t			TE_t		
	Estimate	z value	Significance	Estimate	z value	Significance	Estimate	z value	Significance
(Intercept)	-2.09318	-1.4546		-3.8793	-5.8944	***	-4.52054	-3.4166	***
$lnOutput_t$	0.353191	3.7728	***	0.379004	6.3762	***	0.46756	5.2793	***
$Soil_t$	-0.04169	-4.359	***	-0.03211	-3.1791	**	-0.03299	-3.3967	***
$CropShare_t$				0.469053	2.2075	*			
$Organic_t$	2.10544	4.1116	***				1.428548	3.4762	***
$SubsShare_t$	-3.05054	-3.0326	**				-1.54704	-2.0332	*
$ESubsShare_t$	-2.00789	-3.9171	***				-1.29849	-2.7871	**

Notes:
(i) CE, AE, and TE stand for cost, allocative, and technical efficiency, respectively;
(ii) z values are heteroskedasticity and autocorrelation consistent (HAC) ones;
(iii) significance codes for respective p-values: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1.

Both production and equipment subsidies are likely to cause decrease in cost and technical efficiency, albeit they do not significantly affect allocative efficiency. These phenomena might be linked to excessive purchases of long-term assets. On the other hand, equipment subsidies tend to distort the input market and thus inflate prices of the traded inputs, viz. machinery, buildings. Furthermore, farms receiving higher production subsidies might be located in less favoured areas, where they are subject to lower productivity due to agro-climatic conditions.

As one can note, farmer's age had no significant impact on probability to experience efficiency increase. To conclude, large livestock farms adopted organic farming practices are those most likely to exhibit an increase in productive efficiency.

4. 3. Parametric analysis of the agricultural efficiency

This section fits the stochastic production frontier to the micro data describing the performance of the Lithuanian family farms during 2004-2009 in order to define the current trends of efficiency and productivity in the sector. The stochastic frontier analysis (SFA) is the econometric technique employed for the latter purpose. Specifically, the technical efficiency scores, output elasticities, and the total factor productivity change were estimated.

4. 3. 1. Preliminaries for the econometric analysis of productivity

The following sub-sections present some additional computations related to the econometric analysis of the productive efficiency. Specifically, the TFP change estimation and decomposition is discussed alongside with tests for RTS.

4. 3. 1. 1. Total factor productivity change

The economic performance can be evaluated in terms of efficiency and productivity. Whereas efficiency defines the distance between a certain production plan and respective production frontier, productivity is related to the very location of the frontier. Accordingly, productivity measure describing the multi-input and multi-output technology is referred to as the total factor productivity.

Recall that 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:

$$\ln y_k = \ln \beta_0 + \sum_{i=1}^{m} \beta_i \ln x_i^k + v_k - u_k, \tag{54}$$

where $k=1,2,\ldots,K$ denotes the k-th farm, y and x are output and input quantities, respectively, and $i=1,2,\ldots,m$ stands for the i-th input; $v_k \sim iidN(0,\sigma_v^2)$ is the statistical noise term accounting for measurement errors etc., and $u_k \sim iidN^+(0,\sigma_u^2)$ is the inefficiency term. The technical efficiency of the k-th farm is given by $TE_k = exp(-u_k)$, with $TE_k = 1$ for efficient farms and $TE_k \in (0,1)$ otherwise. Indeed, only the whole error term $e_k = v_k - u_k$ can be observed. Since the inefficiency term, u_k, cannot be observed directly, it is predicted by its conditional expectation with respect to the value of e_k: $E(u_k \mid e_k)$ (Coelli et al., 2005; Latruffe et al., 2004). Battese and Coelli (1988) further employed $E(u_k \mid e_k)$ to predict the firm-specific efficiency:

$$TE_k = E\left\{\exp(-u) \mid y^k\right\} = \left[\Phi\left(\frac{u_k^*}{\sigma_*} - \sigma_*\right) \Big/ \Phi\left(\frac{u_k^*}{\sigma_*}\right)\right] \exp\left\{\frac{\sigma_*^2}{2} - u_k^*\right\},$$

where $u_k^* = -(\ln y^k - \mathbf{x}^k \boldsymbol{\beta})\sigma_u^2 / \sigma$ and $\sigma_*^2 = \sigma_v^2 \sigma_u^2 / \sigma^2$. Note that $\mathbf{x}^k \boldsymbol{\beta}$ is the deterministic part of the production frontier.

The translog (Transcendental Logarithmic) production function is a generalization of the Cobb–Douglas function:

$$\ln y_k = \beta_0 + \sum_{i=1}^{m} \beta_i \ln x_i^k + \frac{1}{2} \sum_{i=1}^{m} \sum_{l=1}^{m} \beta_{il} \ln x_i^k \ln x_l^k + v^k - u^k, \tag{55}$$

with symmetry imposed by setting $\beta_{ij} = \beta_{ji}$. In case one analyzes the longitudinal data. The time index t is introduced. Furthermore, the non-neutral technical change can be tackled by considering the time factor as an input in Eq. 55:

$$\begin{aligned} \ln y_k^t = {} & \beta_0 + \sum_{i=1}^{m} \beta_i \ln x_i^{kt} + \frac{1}{2} \sum_{i=1}^{m} \sum_{l=1}^{m} \beta_{il} \ln x_i^{kt} \ln x_l^{kt} \\ & + \beta_t \ln t + \sum_{i=1}^{m} \beta_{it} \ln x_i^{kt} t + \frac{1}{2} \beta_{tt} t^2 + v^k - u^k \end{aligned}, \tag{56}$$

where t denotes a respective time period. The term 'non-neutral' means that the TC affects the technology in the sense that either the input–mix or the overall productivity becomes time–variant. Accordingly the TC can be input–saving or input–consuming.

The Malmquist productivity index can be employed to estimate total factor productivity (TFP) changes of a single firm over the two periods (or *vice versa*), across two production modes, strategies, locations etc. In this study we shall focus on output–oriented Malmquist productivity index and apply it to measure period–wise changes in TFP. The output–oriented Malmquist productivity index due to Caves et al. (1982) is defined as

$$M_o = \left(M_o^0 \cdot M_o^1\right)^{1/2} = \left(\frac{D_o^0\left(x^1, y^1\right)}{D_o^0\left(x^0, y^0\right)} \frac{D_o^1\left(x^1, y^1\right)}{D_o^1\left(x^0, y^0\right)}\right)^{1/2}, \tag{57}$$

where $D_o^\tau\left(x^\tau, y^\tau\right), \tau = \{0,1\}$ is the Shepard efficiency measure (distance function) with indices 0 and 1 representing respective time periods. The two terms in brackets follows the structure of Fisher's index. Consequently a number of studies attempted to decompose the latter index into different terms each explaining certain factors of productivity shifts. Specifically, Färe et al. (1992) decomposed productivity change into efficiency change (EC or catching up) and technical change (TC or shifts in the frontier):

$$M_o = EC \cdot TC, \tag{58}$$

where

$$EC = D_o^1\left(x^1, y^1\right) / D_o^0\left(x^0, y^0\right), \tag{59}$$

and

$$TC = \left(\frac{D_o^0\left(x^1, y^1\right)}{D_o^1\left(x^1, y^1\right)} \frac{D_o^0\left(x^0, y^0\right)}{D_o^1\left(x^0, y^0\right)}\right)^{1/2}. \tag{60}$$

EC measures the relative technical efficiency change. The index becomes greater than unity in case the firm approaches frontier of the current technology. TC indicates whether the technology has progressed and thus moved further away from the observed point. In case of technological progress, the TC becomes greater than unity; and that virtually means that more can be produced using fewer resources. Given the Malmquist productivity index measures TFP growth, improvement in productivity will be indicated by values greater than unity, whereas regress – by that below unity.

The distance functions involved in Eqs. 59–60 can be approximated by employing SFA (Fuentes et al., 2001; Coelli et al., 2005). Let t and s denote the two adjacent time periods. The technical efficiency can be obtained via $TE_k^t = E\left(\exp(-u) \mid e_k^t\right)$. The latter measure, indeed, is an estimate of the distance function, such that $D_o^\tau\left(x^\tau, y^\tau\right) = TE_k^\tau, \tau = \{t, s\}$. Specifically, the EC component between the two time periods, t and s, is then computed as follows:

$$EC = TE_k^s / TE_k^t. \tag{61}$$

Meanwhile, the TC component can be obtained by the virtue of the following equation:

$$TC = \exp\left(\frac{1}{2}\left(\frac{\partial y_k^t}{\partial t} + \frac{\partial y_k^s}{\partial s}\right)\right). \quad (62)$$

In case the underlying technology is VRS one can also identify the scale efficiency component. The total factor productivity change is obtained by multiplying the EC and TC obtained from Eqs. 61 and 62:

$$TFP = EC \cdot TC. \quad (63)$$

The values of the three measures discussed above become greater (lower) than unity in case of technological progress (regress).

4. 3. 1. 2. Returns to scale and SFA

The econometric approach allows one to estimate the partial output elasticities with respect to different inputs. Specifically, output elasticity with respect to the time trend captures the technological change. The partial elasticity indicates the percentage change of output caused by one per cent increase in a certain input. In case of the translog production function, the partial output elasticity with respect to the *i*-th input, ε_i^k, is obtained by differentiating the production function with respect to a certain input:

$$\varepsilon_i^k = \frac{\partial \ln y_k^t}{\partial \ln x_i^{kt}} = \beta_i + \sum_{l=1}^{m} \beta_{il} \ln x_l^{kt} + \beta_{it} t. \quad (64)$$

Meanwhile, the total output elasticity, ε_k, is the sum of the partial elasticities:

$$\varepsilon_k = \sum_{i=1}^{m} \varepsilon_i^k, \quad (65)$$

with value greater than unity indicating increasing returns to scale (IRS), that equal to unity indicating constant returns to scale (CRS), and that lower than unity indicating decreasing returns to scale (DRS). Note that these elasticities are firm- and time-variant ones. Therefore, they can also be evaluated at the sample means or one can consider their means.

The linear hypothesis of constant returns to scale technology can be tested by constructing a t statistic (Bogetoft, Otto, 2011). Let θ be a column vector of the Maximum Likelihood estimates for a translog function and λ be a row vector of the same dimension with values of unity for elements corresponding to beta coefficients in θ and zeros otherwise. Furthermore, let V be the variance matrix of parameters, viz. betas. The variance of the sum of parameters is then calculated as $Var(\lambda\theta) = \lambda Var(\theta)\ \lambda^T = \lambda V \lambda^T$. The test statistic for the null hypothesis that $\lambda\theta$ equals unity, i. e. the underlying technology is CRS, is given by

$$S = \frac{\lambda\theta - 1}{\sqrt{\lambda V \lambda^T}}, \tag{66}$$

which follows the *t* distribution. In case $S > t(\alpha/2, K-(m+1)-(m+1)^2)$ the underlying technology is IRS, whereas $S < -t(\alpha/2, K-(m+1)-(m+1)^2)$ implies DRS; otherwise CRS is assumed.

4. 3. 2. Production function and technical efficiency scores

The SFA was employed to estimate the efficiency scores for the family farms. The panel data were analysed in a cross-section way (cf. Eq. 56). A series of LR tests was carried out before arriving at the non-neutral model. The labour variable as well as its interactions with remaining ones turned out to be insignificant and thus were removed from the further analysis. This finding might have stemmed from methodological or economic peculiarities. As for the methodological issues, the FADN practice might need some improvements on estimation of the labour amount involved in the agricultural production. Specifically, part-time work can be the hardest observable variable. On the other hand, the Lithuanian family farms might not be eager to report the accurate figures about the paid labour force due to legal regulations.

The final specification of the stochastic translog production function is, therefore, given in Table 7. The time trend is not significant, but indicates a technical progress of some 4.7% per year, whereas the squared trend is negative and a significant one thus inducing that technical progress increases at a decreasing rate. The positive coefficients near interactions between the time trend and intermediate consumption and utilized land area imply that the technical progress was factor-saving in terms of the latter two types of inputs. On the other hand, the negative coefficient associated with trend and asset interaction indicates increasing asset intensity in the production processes.

As one can note, inefficiency accounted for some 67% of the total variation of the error term. The mean technical efficiency (TE) score was 0.76, which implies that output should be increased by some 30% on average.

Table 7. The estimated stochastic production frontier for the Lithuanian family farms (2004–2009)

	Estimate	Standard Error	z value	Pr(>|z|)	
Intercept	5.7128	2.1097	2.7078	0.006773	**
log(Int)	0.7480	0.5585	1.3393	0.180462	
log(Assets)	-1.0967	0.3207	-3.4195	0.000627	***
log(UAA)	1.5083	0.4904	3.0753	0.002103	**
(log(Int) * log(Assets))	0.0724	0.0519	1.3958	0.162764	
(log(Int) * log(UAA))	-0.1731	0.0870	-1.9906	0.046524	*
(log(UAA) * log(Assets))	-0.0001	0.0457	-0.0033	0.997404	
(0.5 * log(Int)^2)	-0.0078	0.1042	-0.0747	0.940471	
(0.5 * log(Assets)^2)	0.0339	0.0433	0.7843	0.432888	
(0.5 * log(UAA)^2)	0.1286	0.0898	1.4315	0.152288	
t	0.0466	0.1146	0.4062	0.684624	
(0.5 * t^2)	-0.0253	0.0080	-3.1427	0.001674	**
(t * log(Int))	0.0221	0.0179	1.2334	0.217425	
(t * log(Assets))	-0.0298	0.0112	-2.6738	0.0075	**
(t * log(UAA))	0.0109	0.0168	0.6451	0.518868	
sigmaSq	0.1808	0.0172	10.5371	< 2.2e-16	***
gamma	0.6665	0.0689	9.6704	< 2.2e-16	***
log likelihood value: -337.2857					
total number of observations = 1200					
mean efficiency: 0.77					

Notes: (i) *Int*, *Assets*, *UAA*, and *t* stand for intermediate consumption, asset value, utilized agricultural area, and time trend, respectively; (ii) significance codes: *** – 0.001; ** – 0.01; * – 0.05.

Fig. 12 depicts the mean values of TE scores across different farming types. Indeed, the farm sample was classified into the three farming type sub-samples in terms of the output structure: Farms with livestock (crop) output accounting for more than 2/3 of the total output were considered as the specialised livestock (crop) farms, whereas the remaining ones were considered as the mixed farms. As one can note, the mean TE had been declining since 2004 and reached its trough in 2006. This particular fall was influenced by unfavourable climatic conditions. After recovering in 2007, the TE further declined during 2008–2009. Noteworthy, the crop farms were specific with higher efficiency fluctuations if compared to livestock or mixed ones. Furthermore, the livestock farms were specific with the highest mean TE scores throughout the research period save year 2004.

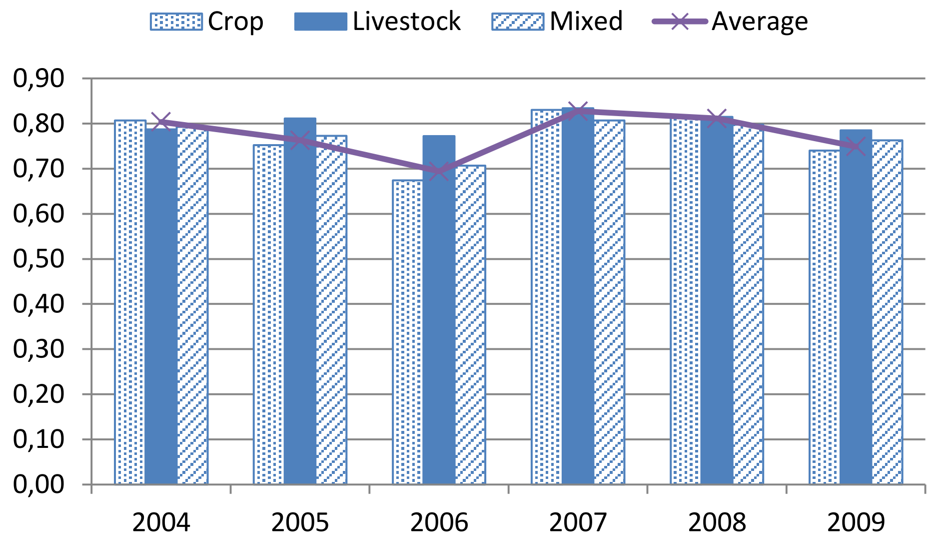

Fig. 12. Mean TE scores across different farming types, 2004–2009

The previous Fig. 12 exhibited the mean values, whereas the underlying distribution of efficiency scores remained unknown. In order to cope with the latter issue, the kernel densities are usually employed in efficiency analyses. This type of graphic representations enables one to avoid arbitrary decisions involved in construction of the other ones (e.g. the different numbers of bins in histograms are related with different visualisations of the same efficiency score distribution). Fig. 13 thus exhibits the underlying distributions of the TE scores across the three farming types. The mean TE scores of each farming type are quite similar: 0.8 for livestock farms and 0.77 for both crop and mixed farms. However, the crop farm distribution is right-skewed and specific with a higher variance if compared to those of the remaining farming types. The lowest variance of the livestock farm TE score distribution implies that these farms are quite homogeneous in terms of technical efficiency, whereas crop and mixed farms tend to be more heterogeneous.

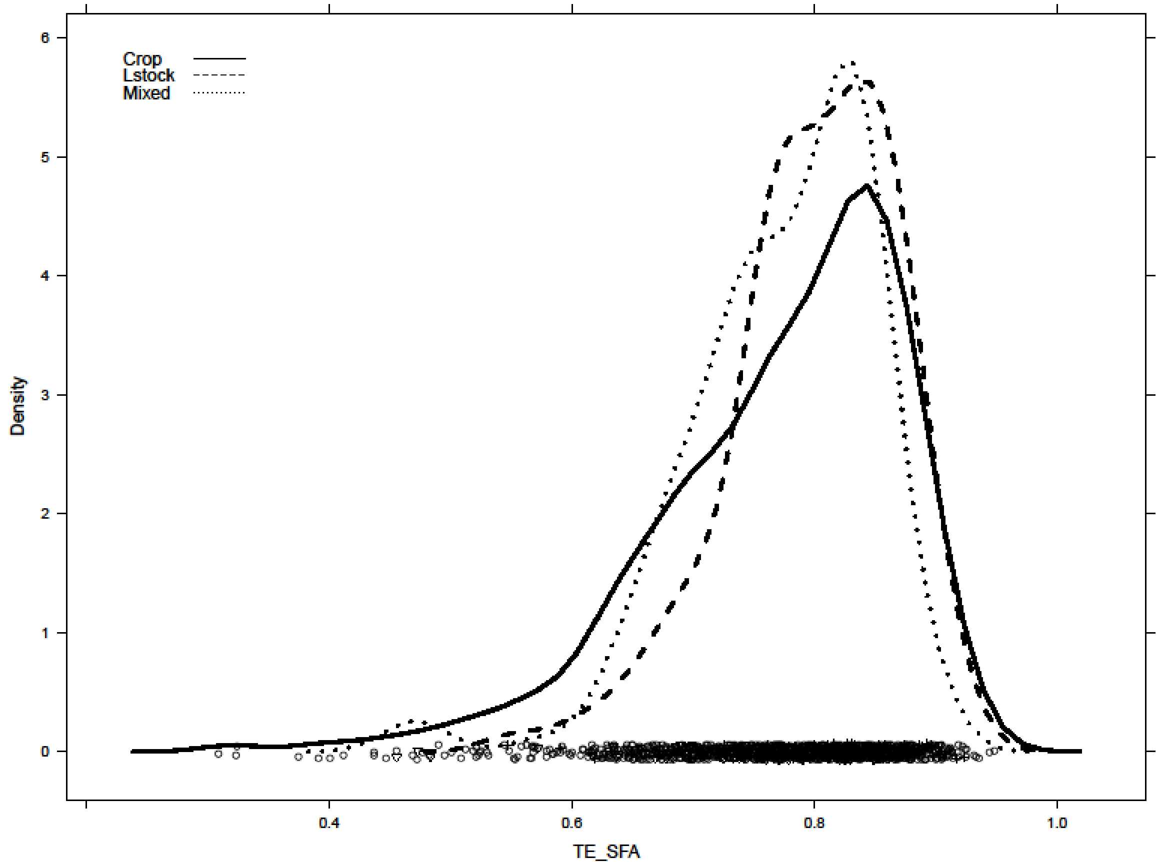

Fig. 13. Kernel densities of the TE scores across different farming types

In order to test whether the differences of the mean TE are significant across farming types, the Least Significant Difference (LSD) test was employed. The results (cf. Table 8) imply that livestock farms had a significantly higher mean of TE scores at the confidence level of 5%. Indeed, the difference between livestock and crop farms was more significant (p=0.001) than that between livestock and mixed farms (p=0.017). Therefore, the mixed farms do benefit from animal farming in terms of efficiency gains.

Table 8. A Least Significant Difference *t* test for means of TE scores across different farming types

Mean Square Error: 0.009139696

	Mean TE	SE	replication	LCL	UCL
Crop	0.7713	0.0034	890	0.765	0.778
Livestock	0.7994	0.0059	137	0.788	0.811
Mixed	0.7733	0.0059	173	0.762	0.785

alpha: 0.05 ; Df Error: 1197
Critical Value of t: 1.961948
Least Significant Difference 0.0182516
Harmonic Mean of Cell Sizes 211.2198

Means with the same letter are not significantly different.

Groups	Treatments	Means
a	Livestock	0.79935
b	Mixed	0.77329
b	Crop	0.77134

Comparison between treatments means

	Difference	pvalue	sig	LCL	UCL
Livestock - Crop	0.0280	0.0014	**	0.0108	0.0452
Mixed - Crop	0.0020	0.8060		-0.0136	0.0175
Livestock - Mixed	0.0261	0.0173	*	0.0046	0.0475

Significance codes: *** – 0.001; ** – 0.01; * – 0.05.

The non-parametric test (Li et al., 2009) was also employed to check whether the underlying densities of the TE are significantly different across the farming types. The non-parametric test did also confirm the difference between the underlying densities of TE scores associated with livestock and crop farming (p=0.02). The differences between densities of the mixed and livestock farms' efficiency scores were significant at p=0.03. Finally, the TE score densities for the crop and mixed farms were different at p<0.000.

To conclude, the livestock farms were specific with the highest technical efficiency. The following sub-sections analyse the main sources and factors of efficiency and total factor productivity.

4. 3. 3. Output elasticities

The partial output elasticities help one to fathom the prospective ways to improve the productive efficiency with respect to the underlying productive technology. The elasticity analysis is related to factor input rationing, for scarce resources should induce higher output elasticities and shadow prices. In the sequel we will analyse the dynamics of the three inputs, viz. assets, intermediate consumption, and land as described in Eq. 64. The time elasticity is to be analysed alongside with the total factor productivity.

The output elasticities with respect to assets are given in Table 9. As one can note, assets became less productive throughout the research period: An additional per cent of assets would have resulted in 0.14-0.27 increase in output in 2004, whereas it would have caused an increase of only 0.1-0.21 in 2009. This finding is alongside with the negative coefficient observed for an interaction between trend and assets. The latter developments might be related with excessive capital use (Petrick, Kloss, 2012), which, in turn, was fuelled by investment subsidies distributed in accordance with the Common Agricultural Policy after Lithuania acceded to the European Union. Noteworthy, it was the mixed farms that were specific with the lowest output elasticity to assets. Indeed, these farms have accumulated the highest amounts of fixed assets. Therefore, the investment support policy should be reconsidered for this particular farming type.

Table 9. Output elasticity with respect to assets, 2004–2009

Year	Farming type		
	Crop	Livestock	Mixed
2004	0.26	0.27	0.14
2005	0.26	0.23	0.17
2006	0.25	0.22	0.15
2007	0.24	0.21	0.16
2008	0.24	0.23	0.13
2009	0.21	0.19	0.10
Average	0.25	0.23	0.14

Elasticity associated with intermediate consumption (Table 10) increased during the period of 2004–2009 from 0.64–0.81 up to 0.75–0.89. The increase might have been driven by improved farming practices, novel chemical products, and successful training programs. The lowest output elasticity to intermediate consumption was observed for the crop farms. Specifically, it constituted some

74–84% of the respective mean elasticity observed for either livestock or mixed farms, depending on which of them was a higher one, during 2004–2009. The crop farms are specific with inflated intermediate consumption values with fertilizer costs accounting for a significant share therein. Therefore, both introduction of new species and application of effective fertilizing schemes are still important for the crop farming. Anyway, the crop farming elasticity associated with intermediate consumption exhibited a positive trend and tended to converge with those specific for livestock and mixed farms.

Table 10. Output elasticity with respect to intermediate consumption, 2004–2009

Year	Farming type		
	Crop	Livestock	Mixed
2004	0.64	0.77	0.81
2005	0.65	0.79	0.77
2006	0.66	0.81	0.79
2007	0.71	0.86	0.84
2008	0.73	0.86	0.86
2009	0.75	0.89	0.88
Average	0.69	0.83	0.83

The output elasticity with respect to utilized agricultural land was generally decreasing from 0.02-0.14 down to 0.01-0.1 during the period of 2004-2009 (Table 11). The range of mean elasticities across farming types, though, remained virtually invariant. The mixed farms were specific with the highest elasticity, whereas the livestock – with the lowest one and even a negative value for year 2008. Indeed, livestock farming does not require land as a production factor to the same extent as other farming types do. There are still some prospects to increase land productivity in the livestock farms mainly by producing fodder.

Table 11. Output elasticity with respect to utilized agricultural area, 2004–2009

Year	Farming type		
	Crop	Livestock	Mixed
2004	0.09	0.02	0.14
2005	0.07	0.05	0.10
2006	0.07	0.05	0.11
2007	0.05	0.03	0.09
2008	0.03	-0.02	0.09
2009	0.04	0.01	0.10
Average	0.06	0.03	0.10

The analysis of the partial output elasticities implies that the Lithuanian family farms face rather meagre difficulties in land acquisition. For the mean partial elasticity associated with land, equal to 0.06, was the lowest one if compared to those associated with intermediate consumption or assets. The marginal asset productivity represented by respective elasticity (0.23) was much higher than that of land, albeit it was down-trended. Therefore, the excessive use of assets should be reduced by streamlining support measures under Rural Development Programme for 2014-2020. Finally, the highest output elasticity was that with respect to intermediate consumption. Indeed, this type of input is the one easy controllable and adjustable.

The total output elasticity was computed in order to test whether the underlying technology is CRS or VRS. The linear hypothesis of CRS was tested in the spirit of Eq. 66. The obtained statistic ($S = 0.85$) was well below the critical value. The null hypothesis about CRS was, therefore, accepted. In the remaining part of the research we therefore did not tackle the scale efficiency.

4. 3. 4. Total factor productivity

The economic performance of a decision making unit should be assessed not only in terms of efficiency but also in productivity. For efficiency measures the firm-specific distance from the production frontier, whereas the total factor productivity describes the shifts of the production frontier. Therefore, a certain firm might not reduce its technological features but become less efficient due to the frontier shift, i. e. increase in the sectoral total factor productivity. On the other hand, a certain firm can maintain the same level of efficiency and become more productive in case it catches up the frontier shift and thus increases its productivity.

The total factor productivity (TFP) change was assessed across the three farming types in terms of Eqs. 61–63. Given the fact that the CRS technology was assumed on a basis of the linear hypothesis test, the TFP change was decomposed into the two terms, namely technical change (TC) and efficiency change (EC). The estimates for each farming type are given in Figs. 14–16.

The crop farms were peculiar with the most intensive fluctuations of the TFP (Fig. 14). The TFP increased during 2004–2005 and 2006–2007, whereas it decreased during 2005-2006 and 2007–2009. The decrease of 2005-2006 was mainly driven by a negative EC effect, what means that unfavourable climatic conditions decreased the TE of the crop farms. The TC, though, did not change if compared to the preceding period and the cumulative change remained greater than unity. Therefore, the production frontier did not move inwards, but the efficiency of an average crop farm tended to decrease. A certain part of the crop farms, nevertheless, remained working as productive as in the preceding period. The EC caused decrease of the TFP to margin of 3%, whereas TC – to that of 10% during the period of 2004–2009. The very TFP decreased by some 13% in the meantime.

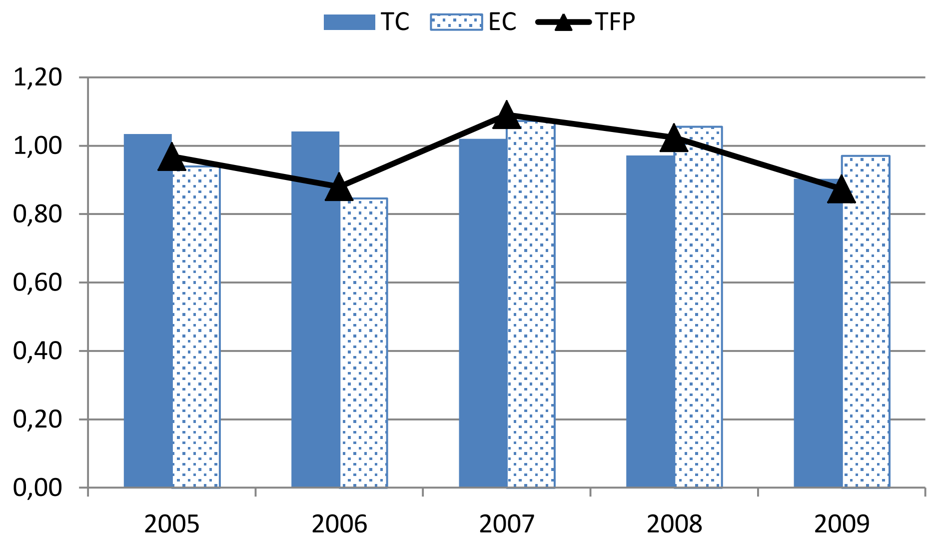

Fig. 14. The cumulative total factor productivity change in the crop farms, 2004–2009

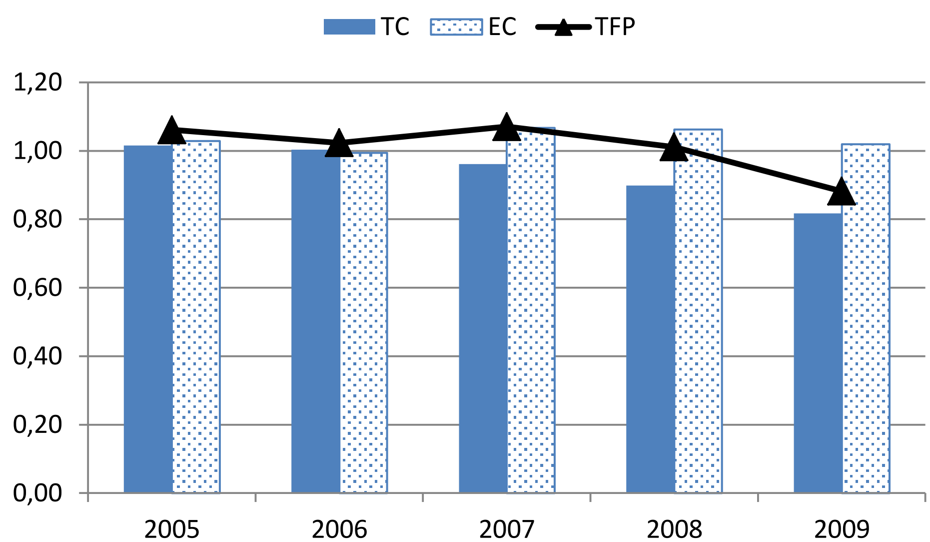

Fig. 15. The cumulative total factor productivity change in the livestock farms, 2004–2009

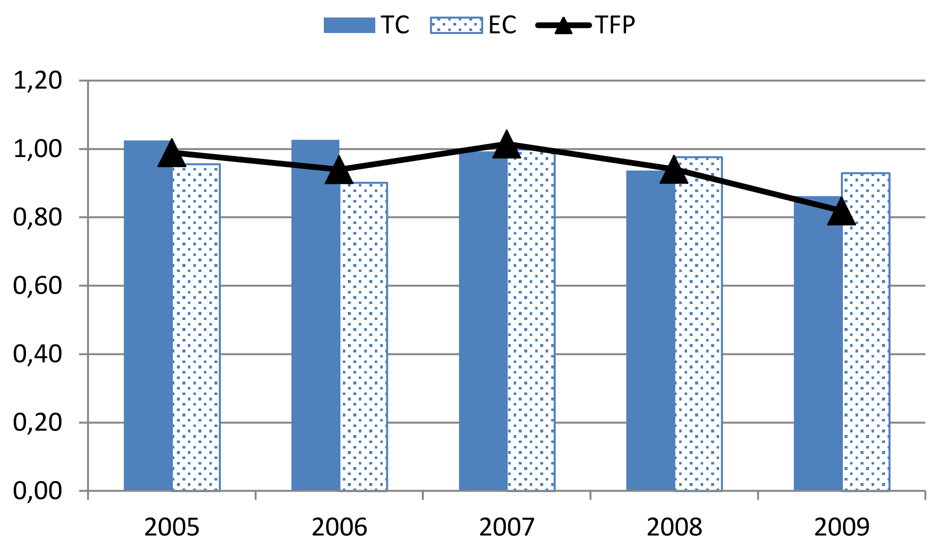

Fig. 16. The cumulative total factor productivity change in the mixed farms, 2004–2009

The livestock farms were specific with the lowest fluctuations in the TFP throughout 2004–2009 (Fig. 15). The latter sub-sector remained virtually unaffected by the downturn of 2005–2006, albeit the subsequent periods were specific with a negative TC trend. Accordingly the TFP began to diminish after year 2007. As a result, the TC resulted in the decline of the TFP by some 18%, whereas the EC component accounted for the increase of some 2%. The resulting TFP change during 2004–2009 was a decrease of 12%. The observed changes in TFP indicate that it was the TC that reduced the TFP, whereas the livestock farms became more homogeneous in terms of the TE, because the cumulative EC remained positive (i. e. that above unity). The decreasing number of livestock is obviously related to the diminishing TFP. The frontier movement inwards could be alleviated by introducing respective support measures aimed at increasing the attractiveness of the livestock farming as an economic activity.

The mixed farming was specific with a degree of the TFP variation that lies in between those of the specialised farms (Fig. 16). Anyway, the mixed farms did not manage to maintain neither the TC level specific for the crop farms nor the EC experienced by the livestock farms. The mixed farming, therefore, was specific with the highest decrease in the TFP accounting for 18%. The results do indicate that the mixed farms should receive more attention when preparing the training and support programs in terms of efficient managerial and agricultural decisions.

4. 4. Comparison of the results

In order to test the robustness of the obtained results one can compare the distributions of the technical efficiency scores obtained by the non-parametric DEA and the parametric SFA. Fig. 17 depicts the relationship between technical efficiency scores obtained by the means of the stochastic frontier analysis and output-oriented DEA model under CRS. Indeed, the VRS assumption results in virtually the same pattern of the efficiency scores.

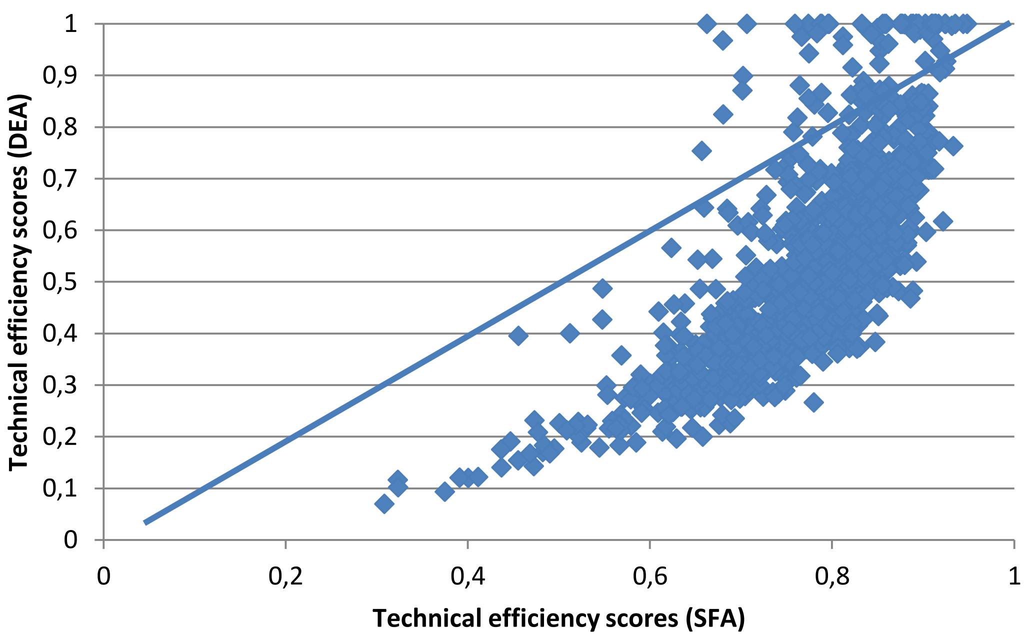

Fig. 17. Comparison of the TE scores obtained by DEA under CRS and SFA

Correlation observed between these two variables was a rather high one (R=0.74). However, Fig. 17 suggests that the relationship is not a linear one. The DEA scores are generally lower that those obtained by SFA, for the former technique considers the whole distance between an observation and the efficiency frontier as that entailed by inefficiency. Furthermore, SFA does not allow a full efficiency, i. e. none of the observations is attributed with technical efficiency score of unity. One more factor is related purely to the methodology of this study: The employed SFA model did not contain the labour input used in DEA model due to statistical insignificance. Anyway, the convergence was achieved in the upper part of the efficiency scores' range.

Fig. 18 presents the mean technical efficiency scores obtained by DEA and SFA across farming types. The correlation observed between these two estimates was extremely high (R=0.99). However, the differences between mean efficiency observed for the livestock farms and that for the remaining farming types are much lower in SFA. It might be a result of the random error term in SFA.

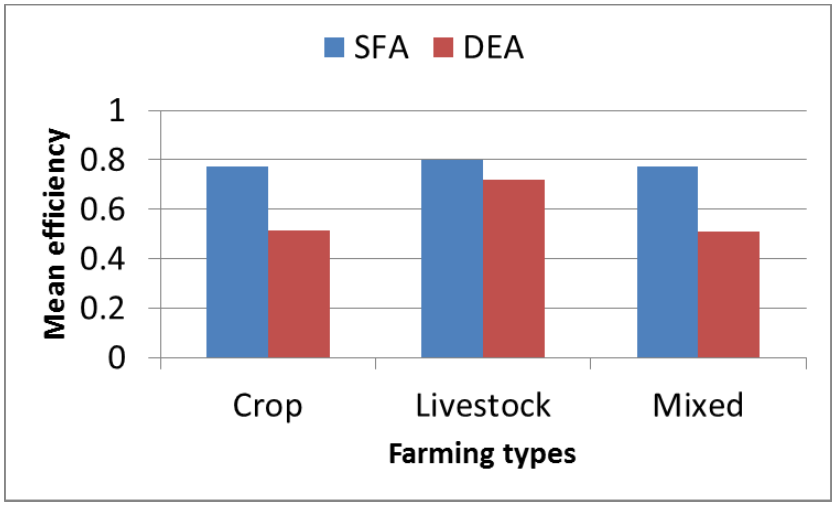

Fig. 18. Variation of the mean technical efficiency scores across farming types

Given the employed dataset contained the longitudinal data, the relation between the efficiency scores obtained by DEA and SFA was analysed across the time periods, namely years 2004–2009. The following Fig. 19 exhibits the results. The entailed correlation was also very high (R=0.9). Both of the employed methods identified the two efficiency shocks in 2006 and 2009.

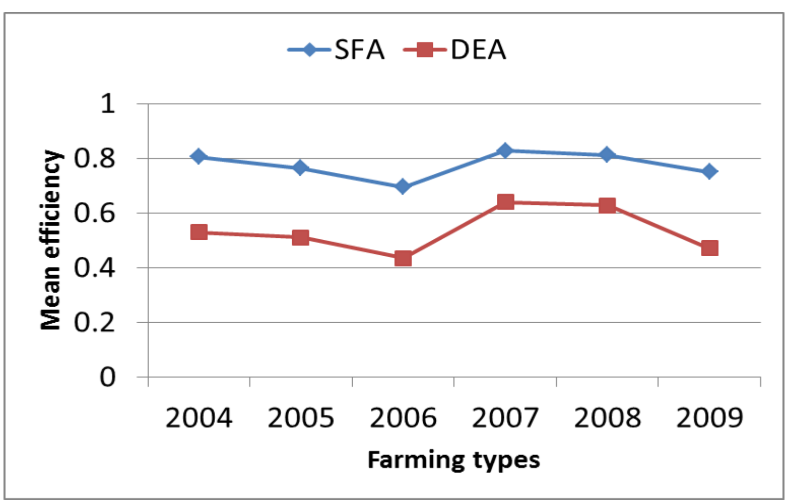

Fig. 19. Variation of the mean technical efficiency scores across years

Both the non-parametric DEA and the parametric SFA identified the same patterns of efficiency in the Lithuanian family farms. The positive correlation was observed for the pooled efficiency scores as well as for the means of the different farming types or time periods. Therefore, the efficiency estimates obtained by the means of DEA and SFA can be considered as the robust ones. Generally, crop farms were specific with lower mean TE values during 2004–2009 if compared to the remaining farming types. Furthermore, the periods of 2006 and 2009 were those of the steepest decreases in TE for all farming types.

CONCLUSIONS

The frontier methods—which, indeed, are the primal techniques employed in this study—enable to analyse the performance of decision making units with respect to multiple criteria describing input consumption and output production. The frontier methods can be grouped into parametric and non-parametric ones. Each of these groups features certain strengths and bottlenecks: The parametric methods enable to estimate the statistical significance of the parameters, whereas the non-parametric ones do not. However, the non-parametric methods do not require any assumptions regarding the functional form of the underlying production frontier. In this study we employed the two celebrated methods belonging to either group of the frontier methods, namely DEA and SFA.

The productive efficiency of Lithuanian family farms was estimated on a basis of FADN data sample by the means of DEA, which did indicate that the mean technical efficiency fluctuated around 65.8%, whereas the mean allocative efficiency approached 70.5%. The mean economic efficiency, therefore, was rather low, namely 46%. These figures imply that Lithuanian family farms should improve both technological and managerial practices and thus achieve higher productivity in order to successfully compete in the single market of the EU.

The second stage analysis of efficiency scores—which, indeed, had not been performed for Lithuanian agricultural sector before—revealed some causes of inefficiency. Specifically, the tobit model was employed to quantify efficiency effects, whereas the logit model was fitted to estimate factors of increase in efficiency. Basically, these analyses showed that large livestock farms adopted organic farming practices are those most efficient. Moreover, they were to exhibit an increase in productive efficiency.

Indeed, crop farming provides intermediate goods for animal farming and thus the latter activity generates higher value added and, thus, is specific with higher efficiency. The new Rural Development Programme for Lithuania 2014–2020 should therefore pay more attention to meat breeding which can further improve attractability of animal farming as well as efficiency of suchlike activities. Furthermore, efficiency indicators should be included in progress reports and constitute a part of monitoring system.

It should be noted that this analysis was based on data from large farms (mean UAA was over 240 ha). Hence, there is a need for further studies on a wider range of family farms. Furthermore, farming efficiency is to be estimated by the means of parametric methods, namely stochastic frontier analysis, which allow more flexibility in tackling heterogeneity related to different farming types.

The paper also fitted the stochastic production frontier to the micro data describing the performance of the Lithuanian family farms during 2004–2009 in order to define the current trends of efficiency and productivity in the sector. Specifically, the technical efficiency scores, output elasticities, and the total factor productivity change were estimated. One of the main limitations of the research was the lack of information on farm production or cost structure.

Out of the initial four input indicators representing land, labour, intermediate consumption, and assets the one associated with labour was dropped due to the resulting insignificancies. Accordingly, this finding might imply that either labour input is the extremely variant one across the observed farms or certain methodological discrepancies do underlie the estimation of this particular variable. The technical efficiency of the Lithuanian family farms fluctuated around 80%. The least significant difference test and the kernel density plots confirmed that the livestock farms were peculiar with the highest mean technical efficiency if compared to that of mixed or crop farms. The high variation specific for the distribution of the technical efficiency scores of the crop farms imply that a significant part of these farms need to improve their practices in order to approach the production frontier. Accordingly, the policy measures aimed at modernization and training schemes are likely to increase the efficiency of the crop farming. The livestock farms were specific with the highest mean technical efficiency.

The estimated partial output elasticities imply that the intermediate consumption was the most productive factor, whereas assets were four to six times less productive depending on the farming type. The land factor was peculiar with the lowest partial output elasticities. The following policy implications related to the factor markets can be drawn from the carried out research. The mixed farms were specific with the lowest partial output elasticities associated with assets. Consequently, the new policy measures should not aim at investments in equipment used there but rather focus on the specialised farms. The lowest output elasticity with respect to the intermediate consumption was observed for the crop farms. These farms, therefore, need to improve their crop-mix as well as fertilizing practice. The partial output elasticity with respect to land was the lowest one and thus indicated that the land market and land use policy need to be further developed in Lithuania.

The total factor productivity change was decomposed into the two terms accounting for the technological and efficiency change, respectively. The results do indicate that the technical change was generally decreasing to a higher extent than efficiency change did. Therefore, the negative trends of technical change might not be compensated even by the upward shifts in efficiency. Both the non-parametric

DEA and parametric SFA identified the same patterns of efficiency in the Lithuanian family farms.

Even though livestock farming is declining in Lithuania, the findings of the paper imply that the latter type of farming exhibited higher efficiency. Indeed, the measures of efficiency are not observed by the farmers and make no impact upon them in the short run. Similarly, the relative measures of efficiency might not be directly linked to the absolute measures of profit which are the main factor affecting farmer decisions. However, the future agricultural policy should pay more attention for increasing the attractiveness and viability of the livestock farming. The latter aims could be achieved by further maintaining the coupled direct payments. In addition the rates of direct subsidies should be revised with respect to farm size and specialization. In particular, the scope of the livestock products supported by the direct payments should be extended in order to create equal economic conditions.

The further studies should tackle the farm heterogeneity by employing panel models or defining separate frontiers for each farming type. In addition, the dynamic technical change assumptions could be imposed by the virtue of the efficiency effects model. The determinants of efficiency can also be further explored by the means of the efficiency effects model. The optimal farm size projections can also be made on a basis of the stochastic production functions. Another important direction for the further researches is international comparisons with certain states specific with similar farming conditions.

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