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PRODUCTIVE EFFICIENCY OF THE LITHUANIAN FAMILY FARMS (2004–2009): A NON–PARAMETRIC INFERENCE WITH POST–EFFICIENCY ANALYSIS

Abstract. *This paper analyses the productive efficiency of the Lithuanian family farms during 2004–2009. The productive efficiency of Lithuanian family farms was estimated on a basis of Farm Accountancy Data Network sample by the means of data envelopment analysis, which did indicate that the average 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 more likely to exhibit an increase in the productive efficiency.*

Keywords: *Efficiency, Family farms, Data Envelopment Analysis, Tobit, Logit.*

JEL Classification: C61, D24, Q12

1. INTRODUCTION

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.

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.

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. Usually the two branches of methods are employed for efficiency analyses, namely non–parametric methods (data envelopment analysis, free disposable hull) and parametric methods (stochastic frontier analysis). These methods can be employed for inter– as well as intra–state comparisons (Hoang and Alauddin, 2012; Ferjani, 2011; Jin et al., 2010; Bojnec and Latruffe, 2011; Aldea, Ciobanu, 2011; Matei, Spircu, 2012). 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.

Although the Lithuanian agricultural sector was analyzed by the means of the non-parametric methods by, for instance, Douarin and Latruffe (2011) and Rimkuvienė et al. (2010), there are still some issues to be tackled. First, all of the previous studies, with exception of Douarin and Latruffe (2011), analyzed the aggregated FADN data rather than micro data. Therefore the aforementioned studies provided fewer opportunities to fathom the underlying trends in both efficiency patterns and farmers' decision-making. Second, Rimkuvienė et al. (2010) analyzed the Lithuanian agricultural sector in terms of performance of the agro sectors of the European Union Member States. Third, the previous studies estimated technical and scale efficiency scores, albeit they did not analyzed cost and allocative efficiency. Our study, therefore, aims at analyzing the micro data by the means of data envelopment analysis (DEA). As a result technical, scale, economic, and allocative efficiency is estimated and subsequently employed in the second stage analysis.

This study aims at analyzing the patterns of efficiency across Lithuanian family farms and thus identifying managerial implications for agricultural policy–making. Indeed, the analysis of productive efficiency can be a seminal part of sustainability management model for the whole agricultural sector in Lithuania ensuring viability of agricultural entities.

The paper is organized as follows. Section 2 presents the main measures of efficiency, whereas Section 3 discusses the non-parametric implementation of these measures by the means of DEA. The following Section 4 describes the data used in the research. Section 5 brings the results of the DEA. Finally, Section 6 is dedicated for the post-efficiency analysis.

2. 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.

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.

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 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. 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:

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

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:

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

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

$$TE_I(x,y) = 1/D_I(x,y) , \tag{10}$$

with $TE_I(x,y) \le 1$ 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:

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

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

$$TE_O(x,y) = 1/D_O(x,y) , \tag{13}$$

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

As it was already said, Farrel (1957) defined the two types of efficiency, which are known as technical and economic efficiency. The economic 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:

$$c(y,w) = \min_x \{w^T x \mid D_I(x,y) \ge 1\} . \tag{14}$$

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

$$CE(x,y,w) = c(y,w)/w^T x . \tag{15}$$

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

$$AE_I(x,y,w) = CE(x,y,w)/TE_I(x,y) . \tag{16}$$

Thus, cost efficiency can be expressed as a product of technical efficiency and cost allocative efficiency. 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. 15). 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 $w^T x^E / w^T(\theta^0 x^0)$.

3. PRELIMINARIES FOR DATA ENVELOPMENT ANALYSIS

The discussed efficiency frontier can be established by employing different computation techniques. 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. 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 do not allow statistical noise and thus the whole distance between the observation and production frontier is explained by inefficiency. In addition, the production frontier (surface) is defined by enveloping linearly independent points (observations) and does not require subjective specification. Therefore non-parametric models are easier to be implemented. Data Envelopment Analysis (DEA) and Free Disposable Hull (FDH) are the two widely renowned non-parametric models.

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.

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. 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 $k = 1,2,...,K$ firms each possessing a certain input-output bundle (x^k, y^k), then the free disposable hull is defined as

$$T = \left\{(x, y) \in \Re_+^m \times \Re_+^n \middle| \exists k \in \{1,2,...,K\}: x \geq x^k, y \leq y^k\right\}. \tag{17}$$

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

$$T = \left\{(x, y) \middle| x = \sum_{k=1}^{K} \lambda^k x^k, y = \sum_{k=1}^{K} \lambda^k y^k, \sum_{k=1}^{K} \lambda^k = 1, \lambda^k \geq 0, k = 1,2,...,K\right\}. \tag{18}$$

By combining assumptions of the free disposability and convexity (cf. Eqs. 17 and 18) the following technology set is obtained:

$$T = \left\{(x, y) \middle| x \geq \sum_{k=1}^{K} \lambda^k x^k, y \leq \sum_{k=1}^{K} \lambda^k y^k, \sum_{k=1}^{K} \lambda^k = 1, \lambda^k \geq 0, k = 1,2,..., K\right\}. \tag{19}$$

The latter technology set includes all points that can be considered as feasible ones under assumption of either convexity or free disposability. DEA method analyses efficiency in terms of suchlike technology set. DEA is a nonparametric method of measuring the efficiency of a decision–making unit (DMU) such as a firm or a public–sector agency.

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 (Hajiagha et al., 2013).

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 $k = 1,2,..., t,..., K$ DMUs, each producing $j = 1,2,..., n$ outputs from $i = 1,2,..., m$ inputs. Hence, the t–th DMU exhibits input–oriented technical efficiency θ_t, whereas output–oriented technical efficiency is a reciprocal number and $\theta_t = 1/\phi_t$. The input–oriented technical efficiency θ_t may be obtained by solving the following multiplier DEA program:

$$\begin{aligned} &\min_{\theta_t, \lambda_k} \theta_t \\ &\text{s. t.} \\ &\sum_{k=1}^{K} \lambda_k x_i^k \leq \theta_t x_i^t, \quad i = 1,2,..., m; \\ &\sum_{k=1}^{K} \lambda_k y_j^k \geq y_j^t, \quad j = 1,2,..., n; \\ &\lambda_k \geq 0, \quad k = 1,2,..., K; \\ &\theta_t \text{ unrestricted.} \end{aligned} \tag{20}$$

In Eq. 20, 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.

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 Eq. 20 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. On the other hand, the best achievable output is obtained by dividing the actual output by the same technical efficiency $\theta_k = 1/\phi_k$, where θ_t is obtained from Eq. 20.

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.

The cost efficiency is obtained by the virtue of the following linear cost minimization model:

$$\min_{\lambda_k, x_i} c(y,w) = \sum_{i=1}^{m} w_i^t x_i$$

s. t.

$$\sum_{k=1}^{K}\lambda_k x_i^k \le x_i, \quad i = 1,2,...,m \tag{21}$$

$$\sum_{k=1}^{K}\lambda_k y_j^k \ge y_j^t, \quad j = 1,2,...,n$$

,

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. 15.

4. 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, 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 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.

5. ESTIMATES OF THE PRODUCTIVE EFFICIENCY

The input–oriented VRS DEA model (Eq. 20) was employed to analyze the FADN data which were arranged into the cross–section table. The cost efficiency estimates were obtained by employing Eq. 21. Finally, the allocative efficiency scores were computed residually. The summary of efficiency scores is presented in Table 1. 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 1 also suggests that the highest variation was observed for the economic efficiency estimates where coefficient of variation was 7.2% for VRS technology.

The intensity variables (peer weights) involved in Eq. 20 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.

Table 1. 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

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. 20 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 $\theta^{CRS} \neq \theta^{VRS} = \theta^{NIRS}$, the DMU operates under DRS. If $\theta^{CRS} \neq \theta^{VRS} < \theta^{NIRS}$, the DMU operates under IRS.

Fig. 1 presents the dynamics of 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%.

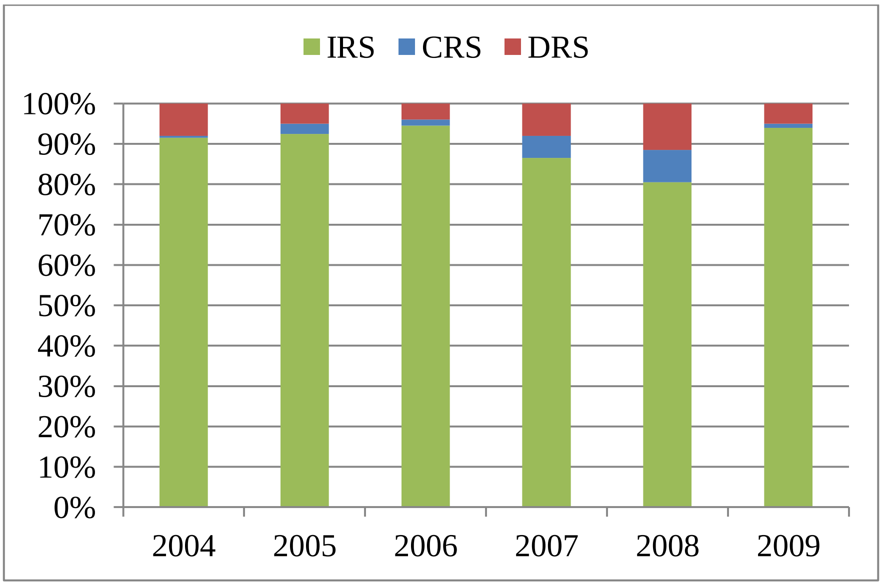

Figure 1. The share of farms experiencing decreasing (DRS), constant (CRS), and increasing (IRS) returns to scale, 2004–2009.

The dynamics of different types of efficiency throughout 2004–2009 is presented in Table 2. 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 1 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 2. Dynamics of the Lithuanian family farm efficiency, 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.

6. 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. 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.

6. 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 (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:

$$E_k = \begin{cases} a, \beta x_k + u_k \le a \\ \beta x_k + u_k, a < \beta x_k + u_k < b \\ b, b \le \beta x_k + u_k \end{cases}, \tag{22}$$

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 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. 22.

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:

$$\frac{\partial EV(E \mid x)}{\partial x_i} = \beta_i \left(\Phi\left(\frac{b - \beta x_k}{\sigma} \right) - \Phi\left(\frac{a - \beta x_k}{\sigma} \right) \right), \tag{23}$$

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 3 and 4 present the fitted tobit model.

As one can note, the autoregressive terms were included in the three tobit models (Table 3) to increase their robustness. The backward procedure was carried out in terms of heteroscedasticity and autocorrelation consistent (HAC) z values. Therefore, Tables 3 and 4 present the significant factors of efficiency. Furthermore, Eq. 23 was employed to estimate marginal effects (the results are available upon request).

Table 3. Coefficients of 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)	-0.07	-1.19		-0.18	-3.61	***	0.33	5.46	***
CE_{t-1}	0.67	16.4	***						
CE_{t-2}	0.10	3.03	**						
AE_{t-1}				0.61	17.44	***			
AE_{t-2}				0.20	5.99	***			
TE_{t-1}							0.55	11.96	***
TE_{t-2}							0.14	3.19	**
$\ln Output_t$	0.23	14.7	***	0.11	10.3	***			
$\ln Output_{t-1}$	-0.21	-12.1	***	-0.089	-7.72	***			
$Soil_t$	-0.002	-2.46	*	-0.001	-2.42	*	-0.002	-2.35	*
Age_t	0.001	3.13	**	0.001	2.72	**			
$Organic_t$	0.047	1.65	.				0.082	2.40	*
$CropShare_t$	-0.048	-2.65	**						
$SubsShare_t$							-0.11	-2.95	**
$SubsShare_{t-1}$	-0.056	-2.88	**						
Log(scale)	-2.33	-41	***	-2.28	-61.4	***	-1.73	-49.7	***

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

The tobit regression (cf. Table 3) 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. 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.

Farmer's age had a positive effect on allocative and economic efficiency, albeit this effect was negative for the youngest farmers. 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 3), whereas the marginal effect at the maximum crop share diminishes to 2.5%. 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 pp. 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.

6. 2. Logit model

The logit model is employed to estimate the following regression:

$$y_k^* = \beta_0 + \sum_i \beta_i x_{ki} + u_k \text{ ,} \tag{24}$$

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

$$y_k = \begin{cases} 1, y_k^* > 0 \\ 0, otherwise \end{cases} . \tag{25}$$

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

$$P_k = F\left(\beta_0 + \sum_i \beta_i x_{ki}\right) \text{ ,} \tag{26}$$

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

$$F(Z_k) = \frac{exp(Z_k)}{1 + exp(Z_k)} \text{ ,} \tag{27}$$

and thus

$$\ln \frac{F(Z_k)}{1 - F(Z_k)} = Z_k \text{ .} \tag{28}$$

As for the logit model, the following equation holds:

$$\ln \frac{P_k}{1 - P_k} = \beta_0 + \sum_i \beta_i x_{ki} \text{ ,} \tag{29}$$

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 4 presents the final results.

Table 4. Coefficients of the logit regression describing shifts in efficiency scores with respect to certain determinants of efficiency.

	Estimate	z value	Sig.
		CE_t	
(Intercept)	-2.093	-1.455	
$lnOutput_t$	0.353	3.773	***
$Soil_t$	-0.042	-4.359	***
$CropShare_t$			
$Organic_t$	2.105	4.112	***
$SubsShare_t$	-3.051	-3.033	**
$ESubsShare_t$	-2.008	-3.917	***
		AE_t	
(Intercept)	-3.879	-5.894	***
$lnOutput_t$	0.379	6.376	***
$Soil_t$	-0.032	-3.179	**
$CropShare_t$	0.469	2.208	*
$Organic_t$			
$SubsShare_t$			
$ESubsShare_t$			
		TE_t	
(Intercept)	-4.521	-3.417	***
$lnOutput_t$	0.468	5.279	***
$Soil_t$	-0.033	-3.397	***
$CropShare_t$			
$Organic_t$	1.429	3.476	***
$SubsShare_t$	-1.547	-2.033	*
$ESubsShare_t$	-1.298	-2.787	**

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

As Table 4 suggests, 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.

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.

7. CONCLUSIONS

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.

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