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TECHNICAL EFFICIENCY AND EXPANSION OF LITHUANIAN FAMILY FARMS (2004–2009): GRAPH DATA ENVELOPMENT ANALYSIS AND RANK-SUM TEST

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The aim of this paper is to estimate the impact of the technical efficiency on farm expansion. The research relies on the sample of the Lithuanian family farms operated throughout 2004–2009. The graph DEA model was employed to estimate the efficiency scores, whereas the rank-sum test was employed to test the relationships between efficiency and expansion variables. Farm expansion was analyzed by considering multiple criteria. The rank-sum test indicated that the farms expanded in terms of ESU and UAA were specific with lower efficiency during the preceding periods. Meanwhile, labour input and assets were not related to different populations of efficiency scores. Therefore, one can expect for decrease in efficiency given no managerial decisions are undertaken.

Key words: efficiency, family farms, expansion, Lithuania, data envelopment analysis.
JEL codes: C440, C610, Q100, Q130.

Introduction

The recent agricultural census indicated certain changes in the Lithuanian farm structure. Specifically, both the number and the area of small farms (up to 100 ha) had decreased in between 2003 and 2010, whereas respective indicators for large farms (over 100 ha) had increased during the same period. As Statistics Lithuania (2012) reports, the number of large farms grew from 2.1 thousand in 2003 up to 3.8 thousand in 2010, what means growth of some 84%. The land area owned by large farms consequently increased to a margin of 74%. The relative importance of the large farms increased at even more rapid pace. As of 2003, the large farms occupied some 26% of the utilized agricultural area (i. e. 2.49 million ha), whereas in 2010 these farms managed to increase their land share up to 42% of the utilized agricultural area which, in turn, had also increased up to 2.74 million ha). The discussed developments lead to increase in the average farm size from 9.3 ha to 13.8 ha throughout 2003–2010. Indeed, these trends can be perceived as an adjustment to the farm structure specific for the developed European Union Member States. Therefore, one can expect for further expansion of the large farms given the agricultural policy will not impose additional incentives for the small farms. In addition, the significant amount of abandoned land does also provide the large farms with opportunities for the further expansion. As of 2010, there were 177–724 thousand ha of abandoned land in Lithuania (Kuliešis, 2011). It is thus important to estimate the possible effect of these developments on the technical efficiency of the Lithuanian agricultural sector.

It is due to A. Alvarez and C. Arias (2004) and M. Gorton and S. 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 (Bogetoft, 2011). Parametric methods aim at fitting the pre-defined production function to the observed data sample given certain assumptions about the distribution of the variables, whereas non-parametric methods define the production frontier by enveloping the most extreme observations. The stochastic frontier methods rely on assumption that inefficiency can be caused by inefficiency as well as random errors. On the other hand, deterministic frontier methods do not allow decomposition of the error term and thus the whole distance between an observation and a production frontier is explained either by inefficiency or random error. Stochastic frontier analysis and data envelopment analysis (DEA) are the two seminal methods for, respectively, parametric and non-parametric analysis. In this study we will employ the graph data DEA.

The Lithuanian agricultural sector was analyzed by employing non-parametric methods viz. DEA and free disposal hull (Vinciūnienė, 2009; Rimkuvienė, 2010; Baležentis, 2012a, 2012b). These studies, however, were based on aggregate data, whereas our research is based on micro data. To be specific, the sample encompasses 200 family farms reporting to the Farm Accountancy Data Network (FADN). The data cover the period of 2004–2009.

The aim of this paper is to estimate the impact of the technical efficiency on farm expansion. The following tasks are therefore set: 1) to discuss the measures of the technical efficiency; 2) to estimate the technical efficiency scores for the analyzed family farms; 3) to analyze the relationships between farm-specific technical efficiency and their expansion. The *R* programming language and package *Benchmarking* (Bogetoft, 2011) were employed to implement the graph DEA model. The rank–sum test was employed to test the relationships between efficiency and expansion variables.

The paper proceeds as follows. Section 1 presents the main measures for productive efficiency and DEA. The following Section 2 describes the rank–sum test. Finally, Section 3 presents results of the analysis.

1. Efficiency measures and DEA

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 (Fried, 2008):

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

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:

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

Similarly, every $x \in \Re^m_+$ has an output isoquant:

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

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:

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

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

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 defined the following input distance function:

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

Here $D_I(x, y) \geq 1$ for all $x \in I(y)$, and $D_I(x, y) = 1$ for $x \in isoI(y)$. 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 $y \in isoO(x)$.

Besides the discussed non-directional efficiency measures there exists a class of directional efficiency measures. Whereas the former methods analyze 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:

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

By simultaneously reducing inputs and expanding outputs with $\alpha>0$ we move the initial point (x_0, y_0) along the hyperbolic curve (the dashed line in Figure 1) until it reaches the efficiency frontier at the point $(\alpha x_0, y_0/\alpha)$.

The mathematical programming models can be employed to estimate the distance functions defined in Eqs. 9 and 12. DEA is among the most important techniques suitable for the latter purpose. The modern version of DEA originated in studies of A. Charnes, W. W. Cooper and E. Rhodes (Charnes, 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, 2007).

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

$$
\begin{aligned}
&\max_{\phi_t, \lambda_k} \phi_t \\
&\text{s. t.} \\
&\sum_{k=1}^{K} \lambda_k x_i^k \leq x_i^t, \quad i = 1,2,...,m; \\
&\sum_{k=1}^{K} \lambda_k y_j^k \geq \phi_t y_j^t, \quad j = 1,2,...,n; \\
&\lambda_k \geq 0, \quad k = 1,2,...,K; \\
&\phi_t \text{ unrestricted.}
\end{aligned} \tag{15}
$$

In Eq. 15, 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, 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. 15 with a convexity constraint $\sum_{k=1}^{K} \lambda_k = 1$.

We can now define the mathematical programming problem in the spirit of Eq. 14. Thus the graph DEA model defining simultaneous treatment of both inputs and outputs has the following form:

$$
\begin{aligned}
&\min_{\varphi_t,\lambda_k} \alpha_t \\
&\text{s. t.} \\
&\sum_{k=1}^{K} \lambda_k x_i^k \leq \alpha_t x_i^t, \quad i = 1,2,...,m; \\
&\sum_{k=1}^{K} \lambda_k y_j^k \geq \frac{1}{\alpha_t} y_j^t, \quad j = 1,2,...,n; \\
&\lambda_k \geq 0, \quad k = 1,2,...,K; \\
&\alpha_t \text{ unrestricted,}
\end{aligned}
\tag{16}
$$

where α_t is the efficiency score for the t-th DMU. Therefore, a certain DMU has to reduce the inputs and expand the outputs by factors α_t and $1/\alpha_t$, respectively. The following Fig. depicts the underlying computations for the graph DEA.

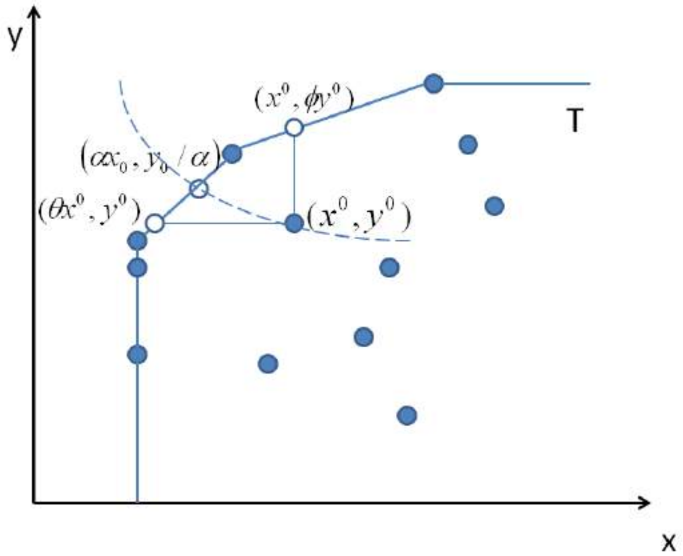

Fig.. The graphical interpretation of DEA.

The production frontier, T, in Fig. 1 is defined by the virtue of Eqs. 4–5. The DEA estimates the efficiency score for the observation (x_0, y_0). In case of the input–oriented DEA one would seek to scale down the inputs by a factor (efficiency score) of θ and thus arrive at the efficient point $(\theta x_0, y_0)$. In case of the output–oriented DEA, one would have to increase the outputs by a factor of ϕ to approach the efficiency frontier at the point $(x_0, \phi y_0)$. Finally, the graph DEA maintains a non–linear movement to the point $(\alpha x_0, y_0 / \alpha)$, where both inputs and outputs are scaled to the different directions.

2. The Wilcoxon rank–sum test

The Wilcoxon rank sum test is a non–parametric technique to compare the distributions of the two samples characterized by a certain explanatory variable. Thanks to its non–parametric nature, the rank–sum test analyzes solely the order in which the observations from the two samples fall (Wild, 2000; Cooper, 2007). As Hoff (2003) argued, the latter peculiarity is of high importance when dealing with DEA efficiency scores, for these do often not follow a specific distribution.

The rank–sum begins by defining two samples of efficiency scores. Let *α* and *β* be the two sets of variables (efficiency scores) with respective cardinalities, *m* and *n*:

$$\alpha = \{\alpha_1, \alpha_2, ..., \alpha_m\} \text{ and } \beta = \{\beta_1, \beta_2, ..., \beta_n\} \tag{17}$$

The we combine these two sets into a single sequence *S* with length $m+n$. Then the elements of the *S* are arranged in ascending order, so that:

$$S = \{s_{(1)}, s_{(2)}, ..., s_{(m+n)}\}, s_{(i-1)} \le s_{(i)} \text{ for } \forall i = 2,3,...,n+m, \tag{18}$$

where $i = 1,2,...,m+n$ is rank denoting the *i*–th largest score. In case two or more scores are equal one needs to use ties. Ties are defined as the mean of the ranks of the equal scores. Having in mind that each element in *S* corresponds to a certain element of *α* or *β*, we can calculate the sums of ranks for each of the two initial samples:

$$SR_\alpha = \sum_{s_{(i)} \in \alpha} i. \tag{19}$$

For the large samples (*N*>12) these variables follow the normal distribution with mean:

$$\mu_\alpha = m(m+n+1), \tag{20}$$

and variance:

$$\sigma = \sqrt{mn(m+n+1)/12}. \tag{21}$$

The reported computations for the sample *β* can be obtained as a straightforward generalization. Therefore, we can obtain the *z* estimate:

$$z_\alpha = \frac{SR_\alpha - \mu_\alpha}{\sigma}, \tag{22}$$

where $z \sim N(0,1)$. This estimate can thus be used to obtain *p* value from the standard normal distribution tables. Accordingly, the null hypothesis, H_0, about the equality of samples *α* and *β* is tested. Meanwhile, the alternative hypothesis, H_1, can be defined in three ways: (i) $H_1 : \alpha \ne \beta$, (ii) $H_1 : \alpha < \beta$, and (iii) $H_1 : \alpha > \beta$. Accordingly, we choose the two– or single–tailed test. In case the obtained *p* value is lower than the required degree of confidence, we reject H_0 about the equality of samples.

3. Data and results

The technical efficiency was assessed in terms of the input and output indicators commonly employed for agricultural productivity analyses. 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 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.

The relative farming efficiency (i. e. technical efficiency) was estimated by the graph DEA method during 2004–2009 (Table). Table 1 also presents the dynamics in the farm size described by European Size Units (ESU, a standard gross margin of EUR 1200) and UAA.

Table. Productive efficiency and mean farm size of Lithuanian family farms (*N*=200), 2004–2009

Year	Technical Efficiency	Farm size (ESU)		Farm size (UAA in ha)	
		Mean	Change	Mean	Change
2004	0.817	34.05		202.1	
2005	0.774	38.25	4.20	226.4	24.3
2006	0.720	49.12	10.86	248.0	21.6
2007	0.827	60.91	11.79	254.9	6.8
2008	0.823	61.31	0.40	265.4	10.6
2009	0.732	66.08	4.77	270.2	4.8
Mean	0.782	51.62	6.40	244.5	13.6

The observed technical efficiency scores generally coincide with those obtained on a basis of the aggregate data (Baležentis, 2012). The steepest decreases in the technical efficiency were observed in 2006 and 2009.

The farm size has increased in terms of both ESU and UAA. Indeed, the economic growth was more significant: the mean size in ESU increased twofold, whereas the mean area increased by some 33%. However, the growth rates fluctuated during the research period. In spite of the increasing intensity of farming, the efficiency scores dropped in 2009 possibly due to external factors.

The rank sum test was further employed to test the links between farm expansion and efficiency at a farm level. The farm expansion was identified by changes in ESU, UAA, labour force (AWU), and assets. Accordingly, the two groups of farms were defined for each of these variables depending individual farms exhibited increase or decrease in a certain variable. Specifically, we analyzed the differences of the efficiency scores for the preceding period across the two groups of farms. For instance, there were 733 observations with increasing ESU during 2004–2009. Each of these observations was attributed with respective efficiency score from the preceding period (2004–2008). Thus, the set of efficiency scores was formed for farms experienced expansion in ESU. Similarly, the set of efficiency scores was defined for farms experienced contraction in ESU. The two sets of efficiency scores were then compared by the means of the rank-sum test (cf. Section 2) to test the impact of farm efficiency on their expansion. In case the expanding farms were specific with higher efficiency scores we could expect an increase in the structural efficiency. Noteworthy, the external shocks might also influence these developments.

The rank–sum test for ESU indicated that expanded and contracted farms significantly differ in their efficiency level. Specifically, the expanded farms were specific with lower efficiency (p=0.017). Therefore, increasing area, herd size etc. was not sufficiently related to increasing revenues from respective farming types. This phenomenon might be caused by inappropriate technologies or unreported income.

The similar trends were also observed regarding the farm expansion in terms of UAA. Those farms experienced increase in UAA were peculiar with lower efficiency scores in the preceding period (p=0.005).

Finally, the rank–sum test indicated that efficiency scores were equally distributed independently of farm expansion in labour input or assets. The null hypothesis of sample equality was accepted at p=0.393 and p=0.73 for labour input and assets, respectively. It might be thus concluded that efficient farms are not likely to increase their assets, albeit further studies are needed to test whether these investments cause shifts in efficiency during the following periods.

What the results do indicate is that large Lithuanian family farms are experiencing rather extensive growth and thus decreasing efficiency. Indeed, Douarin and Latruffe (2011) identified rather similar trends in efficiency change. As they argued, the farm efficiency was likely to decrease due to Single Area Payments which created certain incentives for smaller farms to stay in farming. To cap it all, one needs to develop certain benchmarking systems that would enable to streamline the strategic management of the agricultural sector and thus provide reasonable incentives for increase in efficiency here.

Conclusions

1. The paper analyzed a sample of large Lithuanian family farms in order to relate the patterns of efficiency and decisions on farm expansion. The graph data envelopment analysis was employed to estimate the technical efficiency, whereas the rank–sum test was applied to test whether expanding farms were specific with higher efficiency during the previous period.

2. The farm size has increased in terms of both ESU and UAA. Indeed, the economic growth was more significant: the mean size in ESU increased twofold, whereas the mean area increased by some 33%. However, the growth rates fluctuated during the research period. These findings imply that farming intensity increased to some extent.

3. The rank-sum test indicated that the farms expanded in terms of ESU and UAA were specific with lower efficiency during the preceding periods. Meanwhile, labour input and assets were not related to different populations of efficiency scores. These findings imply that the increasing number and share of large farms is likely to cause some decrease in efficiency given the managerial practices are not improved. Therefore, farm efficiency monitoring systems should be employed to provide decision aiding for allocation of the public support.

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LIETUVOS ŪKININKŲ ŪKIŲ TECHNINIS EFEKTYVUMAS IR PLĖTRA (2004–2009): GRAFŲ DUOMENŲ ANALIZĖ IR RANGŲ SUMOS TESTAS

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Santrauka

Šio straipsnio tikslas – įvertinti ūkininkų ūkių techninio efektyvumo poveikį jų plėtrai. Tyrimas remiasi Lietuvos ūkininkų ūkių, veikusių 2004–2009 m., imtimi. Straipsnyje aptariami techninio efektyvumo matavimo teoriniai aspektai ir matematiniai duomenų apgaubties analizės modeliai, naudoti efektyvumo vertinime. Siekiant įvertinti efektyvumo poveikį ūkių plėtrai, naudotas neparametrinis rangų sumos testas. Ūkių plėtra identifikuota keletu rodiklių. Rangų sumos testas leidžia teigti, kad ūkių ekonominio dydžio (EDV) ir žemės ūkio naudmenų ploto augimas susijęs su mažesniu techniniu efektyvumu ankstesniajame laikotarpyje. Darbo sąnaudų ir ilgalaikio turto rodiklių pokyčiai nebuvo susiję su skirtingais efektyvumo lygiais. Taigi galima teigti, kad, nepriimant papildomų vadybinių sprendimų, ūkininkų ūkių techninis efektyvumas sumažės.

Raktiniai žodžiai: efektyvumas, ūkininkų ūkiai, plėtra, Lietuva, duomenų apgaubties analizė.
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