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STRUCTURAL EFFICIENCY IN LITHUANIAN FAMILY FARMS

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Along with firm-specific technical inefficiency, sector-specific structural inefficiency might induce losses in productivity. This paper therefore aims to identify the trends in structural efficiency in Lithuanian family farms. Specifically, the four farming types are considered, namely cereal farming, field cropping, dairying, and mixed farming. Farm-level data from Farm Accountancy Data Network are used for the analysis. The research period spans over the years 2004–2011. The trends in technical and scale efficiency are presented. Furthermore, the prevailing returns to scale are discussed thus offering insights into the most productive scale size and deviations from it in Lithuanian family farms. Finally, the dynamics in structural efficiency are discussed. The results indicate that the aggregate output of certain farming types could be augmented by some 20–25% due to reallocation of inputs among farms. Anyway, technical inefficiency remains the major driver of structural inefficiency.

Keywords: structural efficiency, technical efficiency, data envelopment analysis, family farms, Lithuania.

JEL Codes: C44, Q12.

1. Introduction

The performance of a certain firm can be measured in terms of its efficiency. Traditionally, efficiency refers to the distance between an observation and a representation of the underlying productive technology (e. g., production frontier, input isoquant, transformation curve etc.). The distance can be measured relative to (the subsets of) inputs, outputs, or both depending on the model's orientation. The resulting measures of efficiency describe firm's performance relative to the given technology, which, in turn, is defined on the basis of the sample of firms. Therefore, the overall situation in a sector is not fully reflected by the means of such firm-specific relative measures.

It was M. J. Farrell (1957) who defined the industry-level measures of structural and aggregate efficiency. The key difference between these two notions lies in the assumption regarding reallocation of resources among firms (Karagiannis, 2015). Indeed, structural efficiency is measured under the assumption that a kind of principal is allowed to redistribute resources across the firms.

On the contrary, aggregate efficiency is measured by assuming that firms exert a complete control over inputs and no changes in the industry structure are allowed. S. K. Li and Y. C. Ng (1995) showed that reallocation efficiency relates structural and aggregate efficiency. Noteworthy, P. Bogetoft and L. Otto (2010) and T. Ten Raa (2011) argued that irrelevant industry structure might cause substantial productivity losses besides firm-specific inefficiency. Therefore, analysis of structural efficiency rewards a substantial attention when seeking for improvements in performance.

The measurement of structural efficiency is closely related to the concepts of the average production unit (APU), average efficiency and aggregate efficiency. APU was defined by F. R. Førsund and L. Hjalmarsson (1974) as a decision making unit (DMU) possessing average input/output quantities over a certain group of DMUs. Accordingly, S. K. Li and Y. S. Cheng (2007) addressed the issues of the meaning of structural efficiency, efficiency of the APU, and differences between average efficiency and efficiency of the APU. In addition, R. Färe and V. Zelenyuk (2003) discussed calculation of the aggregate efficiency.

As regards the practical implementation of the structural efficiency measures, frontier techniques can be used to estimate the underlying technology along with technical efficiency. Data Envelopment Analysis (DEA) is a proper tool to serve the latter purpose. W. Briec et al. (2003) discussed allocation of structural inefficiency across the DMUs by the virtue of shadow price inefficiency (the notion of structural inefficiency in that paper is somewhat different from the one used by, e. g., G. Karagiannis, 2015). A. F. Amores and Ten Raa (2014) analysed Andalusian economy taking into account structural efficiency at different levels of aggregation. J. P. Boussemart et al. (2015) analysed structural performance of Chinese economy. G. Karagiannis (2015) analysed structural efficiency of Greek olive farms.

Therefore, the frontier-based measures of structural efficiency are appealing in several ways. First, they provide insights into productivity losses due to resource misallocation. Second, suchlike framework rests on the principles of neo-classical microeconomic theory. Third, the resulting efficiency measures are aggregate ones and thus allow for inclusion of non-monetary variables into analysis.

Even though frontier measures are widely employed for agricultural sector (Bravo-Ureta, 2007), the issue of structural efficiency has remained neglected in most of the studies. However, public support for agricultural sector might cause reallocation of resources among farms. In particular, the changes in farm structure might be directly related to changes in structural efficiency.

The Common Agricultural Policy is based on support payments which often induce structural changes in the European Union (EU) agriculture. Indeed, the adjustment processes are especially evident in the new EU Member States. For instance, a robust expansion of large farms along with shrinkage in the number of small farms has been observed in Lithuania (Vidickienė, 2014). In this way, farm structure is becoming more similar to that prevailing in the old EU Member States. Therefore, it is important to ascertain whether the recent developments have contributed to structural efficiency of the agricultural sector.

The aim of the research is to identify the patterns of structural efficiency in Lithuanian family farms. The following tasks are set out: 1) to discuss relationships among structural and aggregate efficiencies; 2) to present the frontier models for analysis of structural efficiency; 3) to establish a frontier model based on farm-level data; 4) to describe farm structure in terms of returns to scale; 5) to describe the trends in structural efficiency. The research focuses on the four main farming types in Lithuania, namely cereal farming, field cropping, dairying, and mixed farming. Farm-level data from Farm Accountancy Data Network (FADN) are used for the analysis (Lithuanian …, 2012). The research period spans over the years 2004–2011.

The paper is set out as follows: Section 2 presents the concept of structural efficiency and the related notions along with linear programming models. Section 3 describes the data used. The results regarding technical, scale, and structural efficiency are discussed in Section 4.

2. Preliminaries for measures of structural efficiency

Structural efficiency measures the extent to which the allocation of resources among DMUs ensures that the observed aggregate output quantity corresponds to the potential one (in case of output orientation). More specifically, M. J. Farrell (1957) stressed that structural efficiency should describe the degree to which the constituent firms are of optimal size, high-cost firms are forced to exit, and production is optimally allocated within the sector.

As J. P. Boussemart et al. (2015) pointed out, structural efficiency arises from differences in prices prevailing in different DMUs as stipulated by the second welfare theorem. We will further illustrate this issue graphically. Say there are two DMUs, *A* and *B*. Each of them produces the same amount of output, i.e. $y^A = y^B$. Assume that both of these two DMUs are technically efficient, i.e., they lie on an isoquant in the input space (Fig. 1). As it will be shown in the sequel, the aggregate variable returns to scale (VRS) technology is defined as the sum of individual technologies multiplied by the number of DMUs.

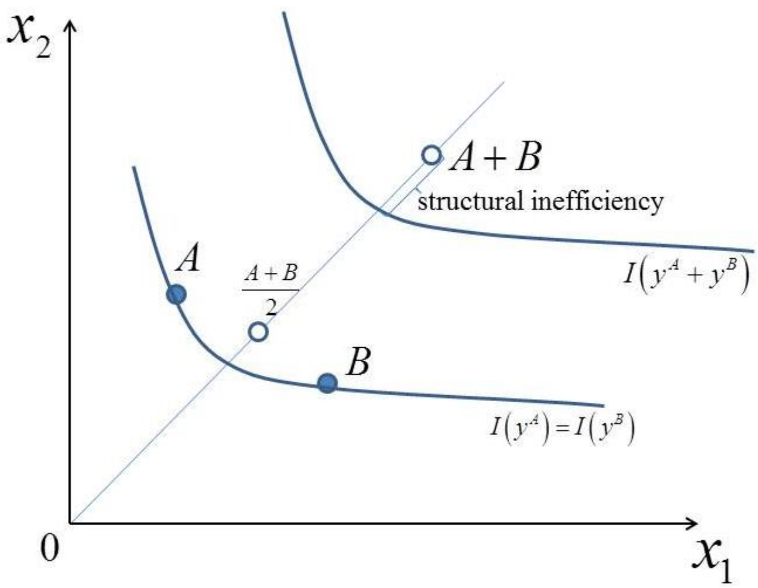

Fig. 1. Structural inefficiency in the input space

Therefore, Fig. 1 depicts the two isoquants: The first one, $I(y^A) = I(y^B)$ is defined for the output level of DMUs A and B. The second one, $I(y^A + y^B)$, defines the aggregate technology. Observation $A+B$ is the composite DMU. Recalling that both observations A and B feature full technical efficiency, we can note that the composite observation, $A+B$, is still inefficient. The gap in performance of the composite DMU is indeed structural inefficiency. Therefore, structural inefficiency is related to different relative input allocations among the DMUs.

Let us now turn to a more dynamic setting, where 0 and t denote the two time periods. Fig. 2 shows the two observations during the two time periods along with the composite observation (assume that the output level remains fixed across the time periods). As observations A and B get more similar in terms of their input structure, the composite observation moves from $A^0 + B^0$ to $A^t + B^t$. As a result, structural inefficiency decreases.

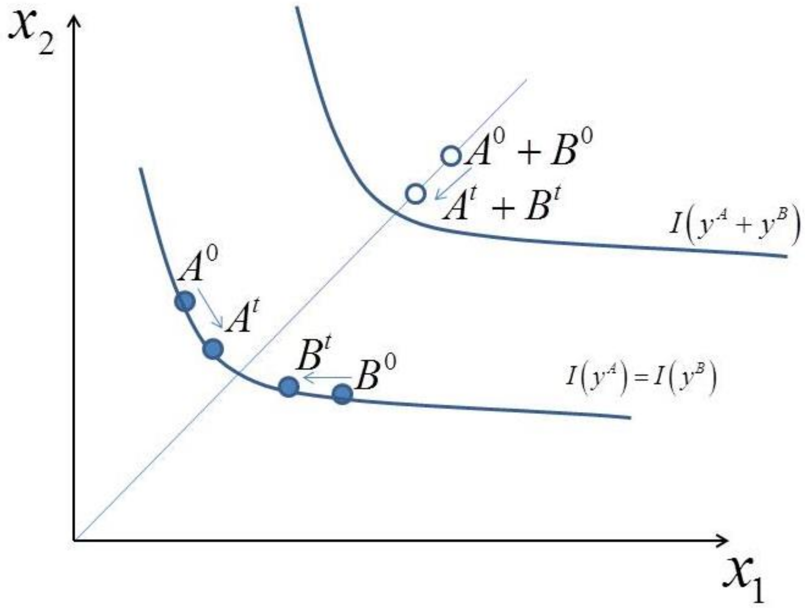

Fig. 2. Dynamics of structural inefficiency in the input space

All in all, an increase in firm homogeneity renders a decrease in structural efficiency. As J. P. Boussemart et al. (2015) put it, an increasing structural efficiency indicates "a convergence to a common expansion path". Therefore, we will apply structural efficiency measures to disentangle the effect of structural changes upon the aggregate (i.e., one computed for a farming type) productivity in Lithuanian family farms.

Formally, the measures of structural efficiency can be described in terms of the productive technology and DEA models. Let a vector of inputs $x = (x_1, x_2, ..., x_m) \in \Re_+^m$ be used to produce a vector of outputs $y = (y_1, y_2, ..., y_n) \in \Re_+^n$. The technology is then defined in terms of a production set:

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

Indeed, T can be represented by input requirement set $I(y)$ and output correspondence set $O(x)$:

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

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

The output-oriented Farrell efficiency measure is defined as follows:

$$E_O(x,y)=\max\left\{\phi\left|(x,\phi y)\in O(x)\right.\right\}. \tag{4}$$

Assume there are K DMUs, indexed over $k=1,2,\ldots,K$. It is due to S. K. Li (1995) that, under constant returns to scale (CRS), the aggregate technology is equal to the individual CRS technology:

$$T_{CRS}=\sum_{k=1}^{K}T_{CRS}^{k}=T_{CRS}^{k}. \tag{5}$$

In addition, assuming a convex technology and VRS, the VRS aggregate technology is given as the individual technology multiplied by *K*:

$$T_{VRS}=\sum_{k=1}^{K}T_{VRS}^{k}=K\cdot T_{VRS}^{k}. \tag{6}$$

Let us define the composite DMU as an input-output vector bundle $\left(\sum_{k=1}^{K}x^k,\sum_{k=1}^{K}y^k\right)$. Following Eq. 6, DEA model (Li, Ng, 1995) can be applied to gauge structural efficiency as efficiency of the composite DMU (in case of output-oriented model):

$$\begin{aligned}
&E_O\left(\sum\nolimits_{k=1}^{K}x^k,\sum\nolimits_{k=1}^{K}y^k\right)=\max_{\phi,\lambda_k}\phi\\
&\text{s.t.}\\
&\sum_{k=1}^{K}\lambda_k x_i^k\le\sum\nolimits_{k=1}^{K}x^k,\quad i=1,2,\ldots,m\\
&\sum_{k=1}^{K}\lambda_k y_j^k\ge\phi\sum\nolimits_{k=1}^{K}y^k,\quad j=1,2,\ldots,n\\
&\sum_{k=1}^{K}\lambda_k=K\\
&\lambda_k\ge 0,\quad k=1,2,\ldots,K
\end{aligned}, \tag{7}$$

where λ_k are intensity variables, $i=1,2,\ldots,m$ and $j=1,2,\ldots,n$ are indexes of inputs and outputs, respectively. S. K. Li and Y. C. Ng (1995) also demonstrated that structural efficiency can also be measured as efficiency of the APU. Indeed, by dividing constraints in Eq. 7 by K and denoting $\zeta_k = \lambda_k / K$, we arrive at the following problem:

$$\begin{aligned}
&E_O\left(\bar{x}, \bar{y}\right) = \max_{\phi, \zeta_k} \phi \\
&\text{s.t.} \\
&\sum_{k=1}^{K} \zeta_k x_i^k \le \bar{x}_i, \quad i = 1, 2, ..., m \\
&\sum_{k=1}^{K} \zeta_k y_j^k \ge \phi \bar{y}_j, \quad j = 1, 2, ..., n \\
&\sum_{k=1}^{K} \zeta_k = 1 \\
&\zeta_k \ge 0, \quad k = 1, 2, ..., K
\end{aligned}, \tag{8}$$

where $\bar{x} = \sum_{k=1}^{K} x^k \big/ K$ and $\bar{y} = \sum_{k=1}^{K} y^k \big/ K$ are the average inputs and outputs, respectively. Therefore, the efficiency scores yielded by Eqs. 6 and 7 are equal. This can also be depicted graphically: an APU points is given as $\frac{A+B}{2}$ in Fig. 1. Hence, structural efficiency can be measured either as efficiency of observation $A+B$ against the aggregate isoquant $I(y^A + y^B)$ or as that for $\frac{A+B}{2}$ against individual isoquants $I(y^A) = I(y^B)$.

Taking the output orientation, aggregate efficiency is measured as a ratio between the potential and observed output of an industry. Recall that structural efficiency rests on the assumption that reallocation is possible, whereas aggregate efficiency looks at the sector-wide efficiency keeping allocation of production among DMUs fixed. This implies that input vectors are not aggregated, whereas aggregate output is considered. R. Färe and V. Zelenyuk (2003) defined aggregate (industry) efficiency for a single-output technology as follows:

$$E_O\left(x^1, x^2, ..., x^K, \sum_{k=1}^{K} y^k\right) = \sum_{k=1}^{K} E_O^k\left(x^k, y^k\right) s_O^k, \tag{9}$$

where $s_O^k = y^k \big/ \sum_{k=1}^{K} y^k$ is the relative weight of the k-th DMU's output and $E_O^k\left(x^k, y^k\right)$ are firm-specific efficiencies. The latter are obtained by the virtue of the following model:

$$
\begin{aligned}
& E_O^k\left(x^k, y^k\right) = \max_{\phi,\lambda_k} \phi \\
& \text{s.t.} \\
& \sum_{k=1}^{K} \lambda_k x_i^k \le x_i^k, \quad i = 1,2,...,m \\
& \sum_{k=1}^{K} \lambda_k y_j^k \ge \phi y^k \\
& \sum_{k=1}^{K} \lambda_k = 1 \\
& \lambda_k \ge 0, \quad k = 1,2,...,K
\end{aligned}
\quad . \tag{10}
$$

S. K. Li and Y. C. Ng (1995) related structural efficiency and aggregate efficiency through reallocation efficiency:

$$
E_O\left(\sum\nolimits_{k=1}^{K} x^k, \sum\nolimits_{k=1}^{K} y^k\right) = E_O\left(x^1, x^2, ..., x^K, \sum\nolimits_{k=1}^{K} y^k\right) \cdot RA\,, \tag{11}
$$

where RA denotes reallocation efficiency. Reallocation efficiency measures the improvement in industry output due to resource reallocation after firm-specific technical efficiency has been netted out. Aggregate efficiency can further be decomposed into the two terms (Olley, 1996):

$$
\begin{aligned}
E_O\left(x^1, x^2, ..., x^K, \sum\nolimits_{k=1}^{K} y^k\right) &= \bar{E}_O + Cov\left(s_O^k, E_O^k\right) \\
&= \bar{E}_O + \sum_{k=1}^{K}\left(s_O^k - \bar{s}_O^k\right)\left(E_O^k - \bar{E}_O^k\right)
\end{aligned}
, \tag{12}
$$

where bars over variables denote respective averages and the second term on the right hand side is a measure of covariance between firm size and efficiency. Therefore, structural efficiency can be expressed as $E_O\left(\bar{x}, \bar{y}\right) = \left(\bar{E}_O + Cov\left(s_O^k, E_O^k\right)\right) \cdot RA$.

3. Data used

The research focuses on the four main types of farming prevailing in Lithuania, namely cereal farming (type 15 under regulation 1242/2008 EC; type 13 under regulation 2003/369 EC), general field cropping (type 16; previously, type 14), dairying (type 45; previously, type 41), and mixed field crops – grazing livestock farming (type 83; previously, type 81). Table 1 below presents the distribution of observation across time periods and farming types. Further details regarding FADN methodology and aggregate results for Lithuania are available in the annual surveys (Lithuanian …, 2012).

The productive technology is modelled in terms of four inputs and one output. The four inputs correspond to labour input in Annual Work Units (AWU), utilised agricultural area (UAA) in hectares, intermediate consumption in Litas, and fixed assets less value of land in Litas.

Table 1. The numbers of observations across farming types and time periods

Farming type	2004	2005	2006	2007	2008	2009	2010	2011	Total
Cereal (15)	513	404	423	427	460	402	403	347	3379
Field cropping (16)	216	205	199	169	141	190	118	149	1387
Dairying (45)	247	179	143	188	215	203	327	330	1832
Mixed (83)	175	221	223	187	218	227	197	204	1652
Total	1151	1009	988	971	1034	1022	1045	1030	8250

The only output variables captures the total agricultural output in Litas. The monetary variables have been deflated by respective real price indices available in Eurostat (base year 2005). However, the application of price indices is only important for intertemporal comparisons. The DEA was applied in a contemporaneous manner in this study. Therefore, the application of price indices does not affect efficiency scores in this case. Anyway, the comparison of farm size in terms of monetary variables across different periods is affected by the application of price indices. Note that Litas (Lt) was replaced by the euro in 2015 (1 euro = 3.4528 Lt).

4. Results

In order to describe structural changes in Lithuanian family farms, we first look at the changes in the absolute variables defining farm performance during the research period. In addition, the degree of variation in the said variables is analysed by the means of coefficient of variation (CV). These measures provide one with insights into the directions and magnitude of farm structural changes.

The average input and output values for the period of 2004–2011 are presented in Table 2.

Table 2. Average values and growth rates of inputs and outputs, 2004–2011

Farming type	Labour input, AWU	UAA, ha	Intermediate consumption, Lt	Assets, Lt	Output, Lt
Average					
Cereal	2.52	223	337841	230970	513943
Field cropping	2.64	152	357272	210821	555195
Dairying	2.67	85	270213	140611	489891
Mixed	2.41	98	210766	125402	410348
Ratio max. to min.	1.11	2.63	1.70	1.84	1.35
Logged rate of growth (%)					
Cereal	31	42	103	87	86
Field cropping	14	19	83	56	67
Dairying	15	11	68	22	58
Mixed	5	29	78	45	56

The data suggest that Lithuanian family farms are similar in terms of labour input (the ratio of maximal average value to the minimal one is 1.11). On the contrary, farms are extremely heterogeneous in terms of UAA (as evidenced by the ratio of

2.63). The difference between maximal and minimal average output values is lower than those for intermediate consumption and assets. Cereal farms appear to be the largest ones in terms of UAA and assets. Field cropping farms feature the highest average intermediate consumption and output. Dairying farms show the highest labour input, which is obviously related to technological peculiarities in the sector and indicate a prospective for further mechanisation and automatisation. Mixed farming is specific with lowest intermediate consumption and output level. However, these variables are absolute ones and are not related to the underlying productive technology.

Looking at the changes in input use (Table 2) reveals that the trends are rather different across farming types and inputs. Cereal farms appear as the largest investors in all the inputs. As regards the latte farming type, the lowest logged rate of growth is observed for labour input, viz. 31%. At the other end of spectrum, the highest rate is 103% for intermediate consumption. Indeed, intermediate consumption shows the highest growth rates for all farming types. Therefore, Lithuanian family farms have been opting for a more intensive farming practice. Obviously, the differences among rates of growth associated with different inputs imply changes in input intensities. Therefore, further studies could attempt to disentangle the underlying trends in technical biases of the productive technology. As for this particular research, it is important to ascertain whether differences in expansion existing among different farming types are related to differences in technical, scale, and structural efficiency.

Table 3 presents the values of CV for different farming types and inputs. Considering the maximal values of CVs, labour input appears as the one for which farms are the most homogeneous (the maximum is observed for field cropping).

Table 3. Coefficients of variation (CV) for different inputs and farming types

Farming type	Labour input, AWU	UAA, ha	Intermediate consumption, Lt	Assets, Lt	Output, Lt
CV for the whole period of 2004–2011					
Cereal	0.82	1.02	1.39	1.38	1.39
Field cropping	0.99	1.15	1.54	1.61	1.58
Dairying	0.83	0.97	1.42	1.38	1.31
Mixed	0.72	1.12	1.50	1.66	1.46
Change in CV (2011 against 2004)					
Cereal	0.23	0.02	0.02	– 0.42	0.12
Field cropping	– 0.04	0.08	0.38	0.13	0.61
Dairying	0.55	0.36	0.68	0.30	0.54
Mixed	0.38	0.23	0.44	0.30	0.47

Indeed, mixed farming features the maximal values of CVs for all of the inputs (a slight discrepancy is observed for assets). Therefore, the latter farming type is specific with the highest diversity in farm size and farming practices. With exception for labour input, mixed farming follows field cropping in the sense of rather high values of CVs for all the inputs. Therefore, these two farming types are rather heterogeneous in farm scale. Similarly, CV for output takes the highest value for field cropping and mixed farming.

Year-specific CVs were also considered in order to define the dynamics in farm heterogeneity. In general, CVs tend to increase over the research period. There are only two exceptions, namely labour input for field cropping and assets for cereals. Noteworthy, the changes in CVs for cereal farms are relatively low if compared to those for the other farming types. It can therefore be concluded that crop farming is likely to approach the most homogeneous pattern of farm scale.

Solving the output-oriented DEA model (Eq. 10) yields the estimates of VRS technical efficiency (TE). By imposing different assumptions regarding returns to scale, one can further decompose the measure of the overall TE into pure TE and scale efficiency (SE). Indeed, the measure of overall TE is related to the CRS technology, whereas that of "pure" TE is obtained relative to the VRS technology. The ratio of the CRS TE over the VRS TE yields scale efficiency. In the output-oriented framework, Farrell measures indicate the proportionate expansion of output quantity needed to ensure full efficiency. The corresponding results are presented in Table 4. Note that the presented measures are based on contemporaneous frontiers. Therefore, the changes in efficiency reflect dynamics in farm homogeneity and possible improvements during a certain time period rather than changes in their performance over the time.

Table 4. Average technical efficiency (TE) and scale efficiency (SE), 2004–2011

Farming type	CRS TE	VRS TE	SE
2004			
Cereal	1.84	1.68	1.11
Field cropping	1.79	1.55	1.19
Dairying	1.54	1.45	1.07
Mixed	1.44	1.36	1.07
2011			
Cereal	2.12	1.90	1.12
Field cropping	1.76	1.59	1.13
Dairying	1.85	1.71	1.10
Mixed	1.66	1.49	1.13
Average			
Cereal	2.14	1.90	1.15
Field cropping	2.14	1.87	1.17
Dairying	1.63	1.51	1.09
Mixed	1.88	1.67	1.15

Table 4 suggests that dairying farms were the most efficient on average (TE score of 1.63 indicates that a 63% increase in output is required on average given the CRS technology). Cereal and crop farms were the most inefficient on average (CRS TE scores of 2.14). The mixed farms fell in between with mean CRS efficiency of 2.14. One can also note that the efficiency scores have generally decreased over time. As TE scores are relative to contemporaneous frontiers, this indicates an increasing homogeneity, whereas no conclusions about the productivity change can be made in such a setting.

Having decomposed CRS TE scores into pure TE and SE, we can note that the main source of loss in productivity (with respect to a contemporaneous frontier) was technical inefficiency rather than scale inefficiency. The ranking of farming types according to the average VRS TE scores is the same as reported above for the CRS TE scores. Obviously, the differences among TE scores across farming types are much more evident than those of SE scores. The average SE scores imply that 9–17% of output could be gained if optimal production scale were achieved. The comparison of SE scores at the two endpoints of the research period with the average ones suggests that SE is more persistent if opposed to TE. These findings imply that SE currently is less severe source of inefficiency if compared to TE in Lithuanian family farms.

In order to identify the patterns of farm performance in terms of the returns to scale prevailing at their operation scale, Table 5 presents the average efficiencies. Note that VRS TE equals to unity in the region of CRS (the same applies for SE). The farms were classified in the spirit of Färe et al. (1983).

Table 5. Average technical efficiency (TE) and scale efficiency (SE) in different regions of returns to scale, 2004–2011

Farming type	VRS TE		SE	
	IRS	DRS	IRS	DRS
2004				
Cereal	1.74	1.65	1.16	1.05
Field cropping	1.80	1.53	1.46	1.13
Dairying	1.47	1.49	1.08	1.06
Mixed	1.41	1.32	1.07	1.09
2011				
Cereal	2.03	1.74	1.16	1.05
Field cropping	1.69	1.50	1.18	1.02
Dairying	1.67	1.75	1.17	1.06
Mixed	1.53	1.48	1.15	1.06
Average				
Cereal	2.01	1.78	1.18	1.09
Field cropping	2.07	1.78	1.23	1.13
Dairying	1.52	1.56	1.13	1.05
Mixed	1.66	1.78	1.20	1.08

The results indicate that cereal and crop farms operating in the increasing returns to scale (IRS) region are less efficient than those in the deceasing returns to scale (DRS) region. Therefore, farms operating at the sub-optimal scale are less efficient if compared to those at supra-optimal scale. Anyway, dairying farms are not that different across the regions of returns to scale: the average efficiency scores for 2004–2011 were 1.52 and 1.56 in the regions of IRS and DRS, respectively. The other farming types show rather similar VRS TE in the region of DRS (1.78), albeit VRS TE tends to vary more in the region of IRS. This implies that small-scale farms are more heterogeneous in their performance across farming types. Turning to SE, one can note that small-scale farms could increase their output by factors of 1.13 and 1.23, whereas these are 1.05–1.13 for farms of excessive scale.

To get insights into the degree of deviations from the optimal scale, Table 6 presents farm structure in terms of the prevailing RTS. Obviously, most of the farms operate under IRS, which corresponds to the sub-optimal scale.

Cereal and mixed farms show the highest shares of farms under IRS, viz. 64% and 62%, respectively (the shares of farms in DRS are the same). Most of the dairying farms (55% on average) operate in the IRS region, i. e. they should expand their operation scale to increase the productivity under the given technology. The average values for field cropping indicate that the latter farming type is specific with the lowest share of farms operating at the sub-optimal scale. The share of farms in the region of CRS is 6%.

Table 6. Farm structure in terms of RTS (per cent), 2004–2011

Year	IRS	CRS	DRS	IRS	CRS	DRS
	Cereal			Field cropping		
2004	56	3	41	20	7	72
2005	70	5	25	38	5	57
2006	61	4	36	50	4	47
2007	74	4	22	58	6	36
2008	66	2	32	39	6	55
2009	72	3	25	73	4	23
2010	50	3	47	33	10	57
2011	67	5	29	70	8	21
Average	64	3	33	47	6	47
	Dairying			Mixed		
2004	60	6	34	68	7	25
2005	69	6	25	53	2	45
2006	70	5	25	46	4	50
2007	40	8	52	64	5	31
2008	63	5	32	74	6	20
2009	44	7	49	61	7	33
2010	60	5	35	55	9	37
2011	43	1	56	74	6	20
Average	55	5	40	62	6	33

Note: rounding errors are present.

The dynamics of farm structure in terms of RTS is rather uneven across time periods. Linear time trends suggest that more decisive changes are observed in the structure of field cropping and dairying farms. In the former case, a negative slope is observed for the share of farms within DRS region, i.e. the share of farms with excessive scale is being reduced by 4.9 p. p. on average each year. The opposite holds for dairying farms: the trend indicates the share of farms with a sub-optimal scale decrease by some 2.6 p. p. each year.

So far, we have described the farm performance across different regions of RTS. However, it is important to identify the main peculiarities of farm size there. Table 7, therefore, presents the main findings in regards to farm size across different regions of RTS. In particular, farm size in the region of CRS corresponds to the most

Table 7. Average input levels across regions of RTS, 2004-2011

	Labour input, AWU			UAA, ha			Intermediate consumption, Lt			Assets, Lt		
	IRS	CRS	DRS	IRS	CRS	DRS	IRS	CRS	DRS	IRS	CRS	DRS
Cereal												
2004	1.5	2.4	2.9	95	265	273	63003	232286	207684	114633	430794	403863
2011	1.8	3.3	5.2	141	330	543	168926	495141	767896	325726	589971	1162194
Average	1.8	2.8	4.0	128	337	397	117727	417459	433981	319928	859909	858964
Log rate of growth	20	34	59	39	22	69	99	76	131	104	31	106
Field cropping												
2004	1.5	1.7	2.7	56	150	170	41112	185315	163437	129394	475072	402484
2011	1.8	4.4	5.0	108	342	336	169047	811480	639103	353778	1411414	1173820
Average	1.6	2.8	3.6	78	203	221	100874	381201	300303	268476	904179	800753
Log rate of growth	21	93	63	65	83	68	141	148	136	101	109	107
Dairying												
2004	2.0	2.3	3.1	54	92	129	50220	136516	159804	160937	460890	632629
2011	1.6	2.1	3.7	58	81	118	87123	382458	252470	227405	759441	570526
Average	1.9	3.2	3.7	54	113	123	73595	279510	215740	264127	1018656	735223
Log rate of growth	– 22	– 10	18	7	– 12	– 9	55	103	46	35	50	– 10
Mixed												
2004	1.9	2.6	3.1	55	113	155	48369	133689	131851	130283	330814	435999
2011	1.7	2.7	4.7	72	115	260	90934	236788	414026	218274	354823	815904
Average	1.7	3.2	3.5	60	185	155	68150	306834	201891	232255	899916	660955
Log rate of growth	– 10	2	41	27	1	52	63	57	114	52	7	63

Note: IRS – increasing returns to scale; CRS – constant returns to scale, DRS – decreasing returns to scale.

optimal scale size, which ensures the highest productivity.

Cereal farms approach the optimal scale with average labour input of 2.8 AWU, UAA of 337 ha, intermediate consumption of 417 thousand Lt and fixed assets of 860 thousand Lt. Note that the monetary terms have been deflated with base year 2005. It is evident that the amount of assets is rather similar for CRS and DRS.

Crop farms (faming type 16) maintain the optimal scale with average labour input of 2.8 AWU, UAA of 203 ha, intermediate consumption of 381 thousand Lt and fixed assets of 904 thousand Lt. In this case, both intermediate consumption and assets show lover values for CRS if compared to DRS.

Dairying farms operate at the optimal scale with average labour input of 3.2 AWU, UAA of 113 ha, intermediate consumption of 280 thousand Lt and fixed assets of 1019 thousand Lt. Note that the amount of assets is rather similar for CRS and DRS. Again, both intermediate consumption and assets show lover values for CRS if compared to DRS.

Finally, mixed farms secure the optimal scale with average labour input of 3.2 AWU, UAA of 185 ha, intermediate consumption of 307 thousand Lt and fixed assets of 900 thousand Lt. For mixed farms, only labour input showed higher average value for DRS if compared against CRS.

The highest differences across CRS and DRS are observed for labour input in cereal and crop farms. These two factors are therefore decisive in determining total factor productivity in the latter farming types. Assets and intermediate consumption feature the highest differences across CRS and DRS in dairying and mixed farms. Lower values for CRS imply that high productivity in these sectors can be maintained by substantial investments in the modern farming practices. Anyway, the ratio of output to inputs remains the highest in the region of CRS in any case. However, we do not proceed with analysis of these indicators for sake of brevity.

Recalling Eq. 11, it is possible to decompose structural efficiency into aggregate efficiency and reallocation efficiency. Furthermore, Eq. 12 enables one to decompose the aggregate efficiency into average efficiency and the covariance term. The following Table 8 presents the average efficiency along with covariance term.

Table 8. Average efficiency and covariance term, 2004–2011

Year	Average VRS TE				Covariance term			
	Cereal	Crop	Dairying	Mixed	Cereal	Crop	Dairying	Mixed
2004	1.68	1.55	1.45	1.36	– 0.26	– 0.26	– 0.09	– 0.12
2005	1.78	1.77	1.40	2.60	– 0.35	– 0.38	– 0.12	– 0.92
2006	1.95	2.21	1.65	1.67	– 0.44	– 0.47	– 0.31	– 0.31
2007	1.80	1.70	1.52	1.51	– 0.29	– 0.25	– 0.20	– 0.25
2008	2.08	2.07	1.41	1.48	– 0.43	– 0.67	– 0.14	– 0.23
2009	1.88	2.19	1.49	1.58	– 0.45	– 0.76	– 0.21	– 0.24
2010	2.20	1.90	1.43	1.54	– 0.68	– 0.60	– 0.17	– 0.28
2011	1.90	1.59	1.71	1.49	– 0.40	– 0.29	– 0.23	– 0.21
Average	1.91	1.87	1.51	1.65	– 0.41	– 0.46	– 0.18	– 0.32

The measures of average efficiency show no clear time trends for either farming type. However, average efficiencies exceed the levels of 2004 in all cases. This indicates an increasing heterogeneity of farms (yet no conclusions about changes in productivity are possible). The ranking of farming types in terms of average efficiency varies throughout the research period. Anyway, cereal farming remains in the last or second-last place during each year. Crop farming showed relatively high TE during 2005 and 2011. The former case is also related to a steep decrease in the efficiency of mixed farms. Turning to the covariance term, one can note that the negative values are observed for each farming type and time period. The negative values indicate a reciprocal relation between farm size and TE. This finding does not match the results in Table 5 as average values for the sub-samples are lower than those delineating the regions of CRS and DRS, for instance.

The sum of average efficiency and the covariance terms equals the aggregate efficiency, which is reported in Table 9 alongside reallocation efficiency. Whereas average and aggregate efficiencies are based on farm-specific measures of efficiency, reallocation efficiency is sector-specific term directly related to input and output structure.

Table 9. Aggregate and reallocation efficiency, 2004–2011

Year	Aggregate efficiency				Reallocation efficiency			
	Cereal	Crop	Dairying	Mixed	Cereal	Crop	Dairying	Mixed
2004	1.43	1.29	1.36	1.23	1.21	1.17	1.19	1.21
2005	1.43	1.40	1.28	1.68	1.19	1.28	1.20	1.23
2006	1.50	1.75	1.34	1.35	1.23	1.43	1.24	1.16
2007	1.51	1.45	1.32	1.26	1.15	1.30	1.18	1.23
2008	1.65	1.40	1.27	1.25	1.20	1.24	1.18	1.19
2009	1.44	1.43	1.28	1.33	1.18	1.22	1.23	1.21
2010	1.52	1.29	1.26	1.25	1.24	1.19	1.16	1.18
2011	1.50	1.30	1.48	1.28	1.18	1.18	1.18	1.18
Average	1.50	1.41	1.32	1.33	1.20	1.25	1.20	1.20

The aggregate efficiency indicates the extent to which the aggregate output of a sector can be expanded due to elimination of farm-specific inefficiencies. Thus, the latter measure is more realistic than that of average efficiency. The aggregate efficiency is rather similar for dairying and mixed farms. Indeed, the average values for 2004–2011 show that an increase in the aggregate output of 32–33% is possible. Field cropping farming appears as the third-best sector with possible improvement of 41%. Finally, an increase of 50% is needed for cereal farms.

Reallocation efficiency is rather stable throughout the time (Table 9). Indeed, its level is also more or less uniform across the farming types. Crop farms show the highest level of reallocation inefficiency, viz. 25%. Therefore, reallocation of inputs among crop farms (farming type 16) leading to an increase in homogeneity of input structure would increase the aggregate output by the same margin. The exceptional situation of crop farms corresponds to the data in Table 3, where the highest variation in input quantities is observed for the same farming type. This implies that differences in absolute input quantities have also been translated into respective differences in relative input structure. As regards cereal, dairy, and mixed farms, reallocation of inputs could render an increase of 50% in the aggregate outputs there. The uniform level of reallocation inefficiency over the time indicates that no convergence mong farms has been achieved in terms of input structure.

The structural efficiency is a product of aggregate and reallocation efficiencies. Table 10 presents the resulting values. Therefore, both farm-specific technical inefficiencies and reallocation inefficiency caused by differences in relative input structure is captured by the measure of the structural efficiency.

Table 10. Structural efficiency, 2004–2011

Year	Cereal	Crop	Dairying	Mixed
2004	1.72	1.51	1.62	1.50
2005	1.70	1.79	1.53	2.07
2006	1.84	2.49	1.66	1.56
2007	1.73	1.88	1.55	1.55
2008	1.99	1.73	1.50	1.48
2009	1.69	1.74	1.58	1.61
2010	1.89	1.53	1.46	1.48
2011	1.77	1.53	1.75	1.51
Average	1.79	1.78	1.58	1.60

The average values of the structural efficiency for 2004–2011 show that dairying and mixed farms are the most efficient ones with possible expansion of the aggregate outputs of some 60%. As regards cereal and crop farms, the corresponding values are some 79%. Noteworthy, these values are lower than average efficiencies, which are usually considered in the analysis (however, this does not apply for dairy farms). The measures of structural efficiency, though, should be considered with caution as these measures are relative to level of the aggregate output. Therefore, even a reallocation of inputs (production) among highly structurally inefficient farms might lead to lower increase in absolute output if compared to some farming types with low structural inefficiency.

5. Conclusions

1. Analysis of the structural efficiency implies that technical inefficiency is more important than reallocation inefficiency. Therefore, a proper application of the existing farming practices is the most topical issue, whereas reallocation of production factors would yield a lower increase in the aggregate output.

2. The average values of the structural efficiency for 2004–2011 show that dairying and mixed farms are more efficient than cereal and crop farms. The results suggest that a possible expansion in the aggregate outputs is 60% for the former farming types and 79% for the latter ones.

3. The processes of large farm expansion in Lithuania did not render significant changes in reallocation efficiency. This implies that reallocation of inputs among

farms within a certain farming type is not likely to cause an increase in the aggregate output of more than 25%.

4. The uniform level of reallocation inefficiency over the time indicates that the shape of the underlying isoquants has not changed significantly over the time. Therefore, no significant convergence has been achieved in terms of relative input structure. Given such inputs as land and labour might become rather scarce in the future, there is a need to analyse the changes in marginal rates of technical substitution, representing substitutability among inputs.

Further research could focus on efficiency gains due to mergers and specialisation. In addition, different assumptions regarding convexity of the productive technology could be taken. Application of such models would allow for gaining additional insights into prospective shifts in efficiency due to structural changes.

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LIETUVOS ŪKININKŲ ŪKIŲ STRUKTŪRINIS EFEKTYVUMAS

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Tiek atskiriems gamintojams būdingas techninis neefektyvumas, tiek sektoriaus mastu egzistuojantis struktūrinis neefektyvumas gali lemti mažesnį produktyvumą. Šio straipsnio tikslas – nustatyti struktūrinio efektyvumo dėsningumus Lietuvos ūkininkų ūkiuose. Tiriami keturi Lietuvoje vyraujantys ūkininkavimo tipai: javininkystė, augalininkystė, pienininkystė ir mišrus ūkininkavimas. Tyrimui naudojami Ūkių apskaitos duomenų tinklo duomenys 2004–2011 m. laikotarpiu, straipsnyje apžvelgiamos techninio ir masto efektyvumo tendencijos. Be to, masto grąžos analizė leido nustatyti optimalų ūkių dydį ir nuokrypių nuo jo mastą bei įvertinti struktūrinį efektyvumą. Remiantis tyrimo rezultatais matyti, kad bendroji atskirų ūkininkavimo tipų produkcija galėtų padidėti 20–25 proc., jei būtų užtikrintas gamybos (veiksnių) perskirstymas tarp ūkių. Techninis neefektyvumas išlieka svarbiausia struktūrinio neefektyvumo priežastimi.

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

JEL kodai: C43, Q12.