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Virginia Namiotko,
Lithuanian Institute of Agrarian Economics,
Vilnius, Lithuania,
E-mail: virginia@laei.lt

Tomas Baležentis,
Lithuanian Institute of Agrarian Economics,
Vilnius, Lithuania,
E-mail: tomas@laei.lt

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DYNAMIC EFFICIENCY UNDER INVESTMENT SPIKES IN LITHUANIAN CEREAL AND DAIRY FARMS

ABSTRACT. Lithuanian agriculture has been receiving investment support under the Common Agricultural policy since 2004. Indeed, the most profitable farming types – cereal and dairy farms – saw a particularly strong increase in the investment amounts. The measure of dynamic efficiency allows one analyze the performance of businesses in regards of inter-temporal optimization of the investment behavior. This paper, therefore, looks into the trends of dynamic efficiency in Lithuanian cereal and dairy farms. The research is based on the data from the Farm Accountancy Data Network covering the period of 2004-2014. The analysis carried out for different farm sizes indicates that scale inefficiency is the main source of technical inefficiency for smaller farms, whether cereal, or dairy ones. Farms experienced investment spikes showed slightly lower inefficiency. These technical efficiency gains are due to improved pure technical efficiency and scale efficiency. However, the latter source appeared as a more important one for the smallest farms (less than 30 ha).

***JEL Classification**:* C44, Q12

Keywords: dynamic efficiency, investment spikes, Lithuania, cereal farms, dairy farms, data envelopment analysis.

Introduction

After Lithuania’s accession to the European Union (EU) in 2004, Lithuanian farmers have been exploiting the advantages of the EU support under the Common Agricultural Policy (CAP). This support has somehow altered the trends in investments and input use. The empirical evidence on the link between investments and productivity is unclear. For instance, Power (1998) found no significant relationship between labor productivity and investments. This implies that investments might not necessarily yield the desirable impacts. Contrarily, Huggett and Ospina (2001) and Sakellaris (2004) revealed that productivity growth initially fall and then later rise after the adoption of a new technology. Bessen (1999) or Janda *et al.* (2013), Bilan & Strielkowski (2015) also found that productivity improves as a result of learning-by-doing. Geylani and Stefanou (2013), Simionescu (2016) showed that the link between investments and productivity depends on investment type. Accordingly, there is a need to explore the effects of investments in Lithuanian family farms where investments have been boosted thanks to the investment support under the measures defined in the CAP schemes. This paper addresses the following question: what are the key trends in cereal and dairy farming efficiency in Lithuania in the context of investment spikes?

Traditionally, productivity and efficiency are studied from a static perspective. This paper, however, relies on the dynamic approach which seeks to link the decisions on input adjustment made within different time periods. The patterns of dynamic efficiency have been widely studied across different countries and sectors (Serra *et al.*, 2011; Rungsuriyawiboon, Hockmann, 2015; Kapelko *et al.*, 2016a, 2016b; Kapelko, Oude Lansink, 2017; Mikócziová, 2010; Krylovas *et al.*, 2016). However, the analysis of dynamic efficiency in Lithuanian agriculture has received much less attention in the literature (Baležentis, 2016). Therefore, the present paper attempts to address the latter gap in the literature. In this paper, we follow the non-parametric approach for estimation of the dynamic efficiency. Specifically, data envelopment analysis (DEA) is employed to construct the production frontiers and obtain the values of the distance functions. The non-parametric approach allows constructing the production frontiers without assumptions on the functional form thereof.

This paper aims to evaluate the underlying trends in cereal and dairy farming efficiency in Lithuania in the context of investment spikes. The following tasks are therefore set: 1) to present the framework for analysis of the dynamic efficiency; 2) to identify the main trends in cereal and dairy farm performance in Lithuania and selected EU countries; 3) to estimate the measures of the dynamic efficiency for a sample of Lithuanian family farms. The research is based on data from the Farm Accountancy Data Network (FADN) covering the period of 2004-2014.

This paper is organized as follows. Section 1 presents the Data Envelopment Analysis model for analysis of the dynamic efficiency. Section 2 discusses the results. Finally, concludes.

1. Methods and data

The research seeks to identify the effects of investments on dynamic efficiency. therefore, the research framework comprises the two main components. First, the DEA model is implemented to obtain the measures of the dynamic efficiency. These measures reflect farm performance in terms of both output production and investment behaviour. Second, investment spikes were identified in order to classify farms into those experiencing serious changes in the fixed asset stocks.

The models for analysis of the dynamic efficiency involve the establishment of certain specific variables along with the conventional vectors of input and output quantities. More specifically, the input vector is divided into the two sub-vectors each comprising variable and quasi-fixed inputs (i.e., capital) respectively. In addition, the quantities of fixed inputs can be considered. The dynamic technology for period *t* can be represented by an input requirement set in the following manner (Silva *et al.*, 2015):

$$V(y^t \mid K^t) = \left\{(x^t, I^t) : (x^t, I^t) \text{ can produce } y^t \text{ given } K^t\right\}, \tag{1}$$

where $y^t \in \Re_{++}^M$ represents a $1\times M$ vector of outputs, $x^t \in \Re_{+}^N$ stands for a $1\times N$ vector of variable inputs, $K^t \in \Re_{++}^F$ denotes a $1\times F$ vector of quasi-fixed inputs, and the dynamic factor is captured by a $1\times F$ vector of gross investments, $I^t \in \Re_{+}^F$. The inefficiency is measured by means of the directional input distance function which, indeed, corresponds to the scaling factor β defining a movement towards an efficient frontier by reducing the level of inputs and increasing the flow of investments for a certain period *t* (Kapelko *et al.*, 2015), see *Fig. 1*. The direction of the movement is actually determined by the directional vector (g_x, g_I).

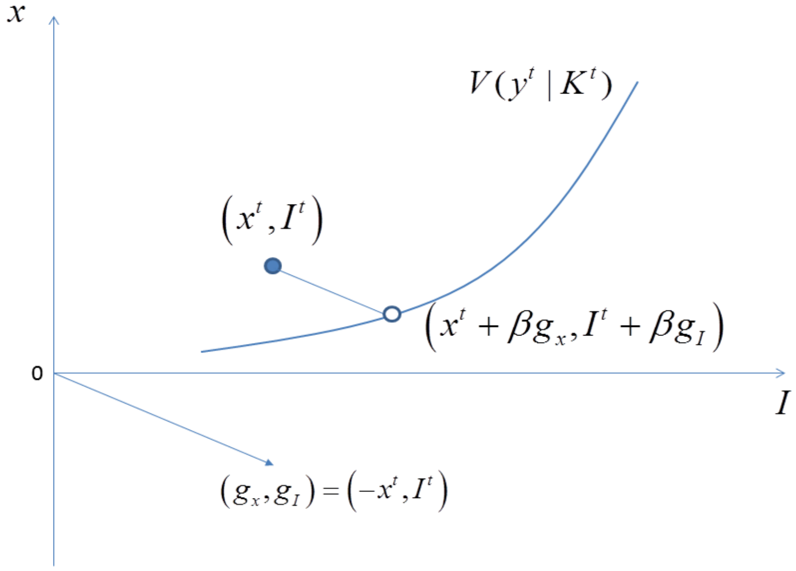

Fig. 1. Dynamic directional input distance function

Fig. 1 depicts a particular case of the projection onto the efficiency frontier in case the direction vector is set to ($-x^t$, I^t). Therefore, an inefficient observation, (x^t, I^t), is projected towards efficiency frontier by reducing input quantities and increasing investments at point $\left(x^t + \beta g_x, I^t + \beta g_I\right)$. Multiplier β indicates the value of directional input distance function, i.e. the level of inefficiency.

Let $D(y,K,x,I;g_x,g_I)$ denote the directional input distance function for observation (y,K,x,I) given directional vector (g_x, g_I). Silva *et al.* (2015) proved the existence of duality between $D(y,K,x,I;g_x,g_I)$ and the current value of the optimal value function of the following inter-temporal cost minimization problem at any base period $t \in [0,+\infty)$:

$$
\begin{aligned}
& W\left(y, K_t, w, c, r, \delta\right) = \min_{x(\cdot), I(\cdot)} \int_t^{+\infty} e^{-r(s-t)}\left[w' x(s) + c' K(s)\right] ds \\
& \text{s.t.} \\
& \dot{K}(s) = I(s) - \delta K(s), K(t) = K_t \\
& \left(x(s), I(s)\right) \in V\left(y(s) \mid K(s)\right), s \in [t, +\infty)
\end{aligned}
\quad , \qquad (2)
$$

Where r and δ are the rates of discount and depreciation, respectively. Indeed, directional input distance function $D(y,K,x,I;g_x,g_I)$ gauges the technical efficiency component of the overall (economic) efficiency.

Practically, the directional input distance function can be computed by implementing DEA model (Silva *et al.*, 2015). The DEA rests on the empirical production frontier which is defined by considering production plans of the K decision making units (DMUs) indexed by

$k = 1, 2, \ldots, K$. The following DEA model renders the value of dynamic directional input distance function (inefficiency) for an arbitrary chosen observation $k' = 1, 2, \ldots, K$:

$$
\begin{aligned}
& D_t(y^t, K^t, x^t, I^t; g_x, g_I) = \max \beta \\
& \text{s.t.} \\
& \sum_{k=1}^{K} \lambda_k y_{m,k}^t \geq y_{m,k'}^t, m = 1, 2, ..., M; \\
& \sum_{k=1}^{K} \lambda_k x_{n,k}^t \leq x_{n,k'}^t + \beta g_{x,n}, n = 1, 2, ..., N; \\
& \sum_{k=1}^{K} \lambda_k \left(I_{k,f}^t - \delta_f K_{k,f}^t \right) \geq I_{k',f}^t - \delta_f K_{k',f}^t + \beta g_{I,f}, f = 1, 2, ..., F; \\
& \lambda_k \geq 0, k = 1, 2, ..., K
\end{aligned} \quad , \qquad (3)
$$

where λ_k are weights of the DMUs (intensity variables) and δ_f is the depreciation rate for the f-th fixed input. Note that Eq. 3 assumes constant returns to scale (CRS) technology.

Depending on the scale of operation, a certain DMU might operate in the region of increasing, constant or decreasing returns to scale. Analysis of the returns to scale might provide insights on the degree and direction of deviation from the optimal farm size in the present study. The qualitative approach enables to classify the DMUs into those operating under increasing, constant, and decreasing returns to scale without calculating the scale elasticity. In order to identify the returns to scale prevailing for each DMU, production frontiers based on different assumptions on returns to scale need to be constructed. Specific assumptions on the returns to scale for the DEA technology can be imposed by manipulating the convexity constraint (i.e. sum of intensity variables) in Eq. 3 (Färe *et al.*, 1983; Färe, Grosskopf, 1985; Grosskopf, 1986). Specifically, $\sum_{k=1}^{K} \lambda_k = 1$ renders variable returns to scale technology, whereas $\sum_{k=1}^{K} \lambda_k \leq 1$ imposes non-increasing returns to scale. The inefficiency scores corresponding for variable returns to scale and non-increasing returns to scale technologies can be denoted as β_{VRS} and β_{NIRS}, respectively. Furthermore, let β_{CRS} be a solution of Eq. 3 which contains no restriction on the sum of the intensity variables. A DMU is said to operate in the region of increasing returns to scale (IRS) if $\beta_{CRS} \neq \beta_{VRS} < \beta_{NIRS}$. Most productive scale size is maintained when $\beta_{CRS} = \beta_{VRS}$. The region of decreasing returns to scale (DRS) is indicated by $\beta_{CRS} \neq \beta_{VRS} = \beta_{NIRS}$.

Farm-level data from FADN are applied for the analysis. We focus on specialised cereal and rapeseed farms falling under faming type 15 according to regulation 1242/2008 EC (resp. type 13 according to regulation 2003/369 EC) and specialised dairy farms falling under faming type 45 according to regulation 1242/2008 EC (resp. type 41 according to regulation 2003/369 EC). The data cover years 2004-2014.

Three variable inputs (land, labour, and intermediate consumption), a quasi-fixed input (capital assets), dynamics factor (gross investments), and an output (total agricultural output) are used to establish the dynamic productive technology. Land input is utilised agricultural area in hectares. Labour input comprises both family and external labour force in annual work units. Intermediate consumption encompasses specific production costs along with overheads (in Lithuanian Litas[1]). Capital assets include the book value of machinery and buildings at the beginning of the year (in LTL). Gross investments represent the flow of investments during the respective year (in LTL). Total agricultural output captures crop, livestock, and other agricultural outputs (in LTL). Törnqvist price indices were applied to derive implicit quantities of capital assets, investments and agricultural output.

The outliers were identified following Geylani and Stefanou (2013). Also, observations with negative gross investments were omitted. As a result, 3671 cereal farm and 2782 dairy farm observations are considered.

Investment spikes were identified following Geylani and Stefanou (2013). Investments exceeding the 2.5 median values of the investment-to-asset ratio for the whole sample are regarded as spike investments.

2. Results

Lithuania has seen a transition in the structure of the agricultural output. More specifically, analysis of changes in gross agricultural output structure in 2004-2014 shows that shares of the livestock output and crop output were virtually the same at the beginning of the period under analysis. Later on, the share of the livestock output started to decrease. In 2014, as compared to 2004, the share of cereals and industrial crops increased to the highest extent in the gross agricultural output structure, while the shares of cattle, poultry, and milk decreased most considerably (Melnikienė, 2016; Statistics Lithuania, 2016).

To illustrate the dynamics in the scale and scope of the crop farming, *Fig. 2* presents the trends in areas sown under the main cereal crops, namely wheat, barely, and rape. Over the period of 2004-2014, the areas sown under wheat and rape had increased, whereas the area sown under barley had decreased. These changes to a great extent were influenced by the grain purchase prices. The purchase price for wheat was by 55% higher in 2014 than in 2004, whereas the corresponding figure for rape was 53%. The selling price for barley showed the lowest increase among these crops.

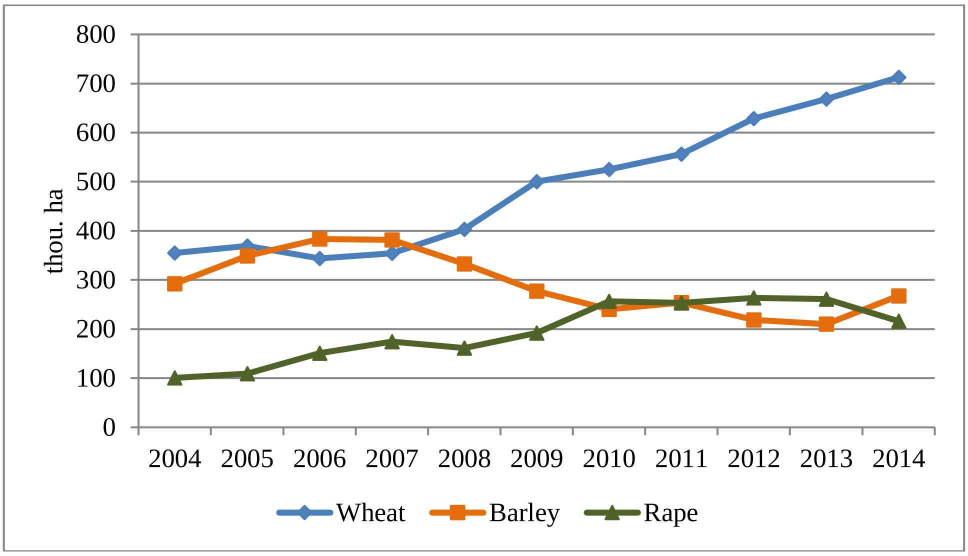

Fig. 2. Crop area of major cereal crops in Lithuania in 2004-2014 (Statistics Lithuania, 2016)

[1] 1 Lithuanian Litas (LTL) equaled 0.2896 EUR until 2015.

The situation in the livestock farming can be illustrated by *Fig. 3*. Indeed, the number of dairy cows decreased persistently throughout the entire period of 2004-2014. The number of the other cattle increased from 358.1 thousand in 2004 to 422.7 thousand in 2014, i.e. by 18%. The main reasons for negative tendencies in the dairy sector are low purchase prices for milk and relatively lower direct payment rates as compared to crop products. The growth in the number of the other cattle can be attributed to increasing popularity of beef farming.

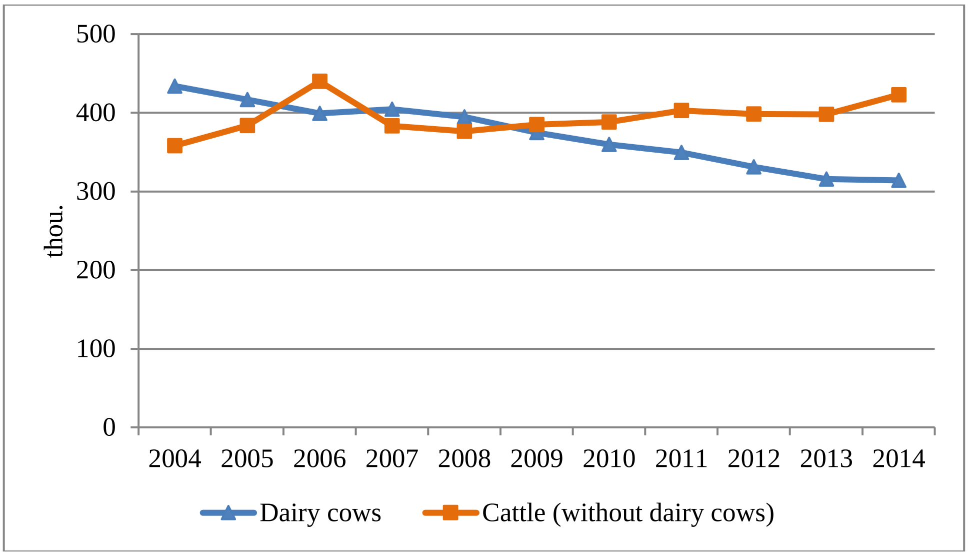

Fig. 3. Number of cattle (without dairy cows) and dairy cows in Lithuania in 2004-2014 (at the end of the year) (Statistics Lithuania, 2016)

The underlying trends in development of Lithuanian cereal and dairy farms were analysed by considering the standard variables from FADN for selected EU Member States. *Tables 1* and *2* present the key production and investment indicators for cereal and dairy farms, respectively. In order to reduce the temporal variation, we consider the average values over the period of 2004-2013.

Table 1. Key production and investment indicators for cereal farms (in EUR/ha), averages for 2004-2013 (European Commission, 2016)

Country	Total crops output	Crop-specific costs	Net investment	Average farm capital	Machinery and buildings	Investment support
Denmark	975	311	224	8942	5702	2
Latvia	500	207	111	898	530	25
Lithuania	530	204	132	1152	668	57
Poland	718	278	39	1886	1358	5
Germany	1042	377	82	1740	1009	1

The results in *Table 1* suggest that the new EU Member States (Latvia, Lithuania, Poland) are worse off if compared to the old EU Member States. The main reason for lower crop output is lower yields of grain crops. Even though the yields of grain crops have been increasing in Lithuania recently, there is still a gap in yields in Lithuania and highly developed European countries. Crop production costs show the same trend as it is observed for crop output and can partially explain the existing yield gap.

The comparison of investment support intensity across the countries shows that, during the period of 2004-2014, the highest investment support intensity was observed in

Lithuania and Latvia (57 EUR/ha and 25 EUR/ha, respectively). However, the average farm capital was the lowest in Latvia and Lithuania (1152 EUR/ha and 898 EUR/ha, respectively).

Table 2 focuses on the production and investment indicators in dairy farms. Clearly, both the livestock and output and production costs are lower in the new EU Member States. In spite of the higher rates of investment support, Lithuania and Latvia show lower values of the average farm capital if contrasted to the old EU Member States.

Table 2. Key production and investment indicators for dairy farms (in EUR/LU), averages for 2004-2013 (European Commission 2016)

Country	Total livestock output	Livestock-specific costs	Net investment	Average farm capital	Machinery and buildings	Investment support
Denmark	1964	1106	440	6525	7622	2
Latvia	906	569	57	2381	491	160
Lithuania	951	479	136	3405	1062	194
Poland	1042	338	79	4304	3246	14
Germany	1617	547	7	3700	2872	71

These findings imply that both cereal and dairy farms in Lithuania lag behind those in the developed countries in terms of both productivity and input use. This suggests Lithuanian cereal and dairy farms still require investments into capital assets. However, it is important to avoid excessive investments. The analysis of dynamic efficiency, hence, might provide insights into the optimal level of investments.

As mentioned before, the support payments under the EU CAP have enabled Lithuanian farmers to invest more in capital assets and thus gave momentum for modernization of agricultural holdings there. By using farm-level data from FADN, we look at the incidence of investment spikes (cf. Section 2) in the sample. *Table 3* presents the number of spike observations in Lithuanian cereal and dairy farms as well as their contribution to total investment.

Table 3. Investment spike characteristics in Lithuanian cereal and dairy farms

Indicator	Cereal farms	Dairy farms
Percentage of observations in data set with spikes	51	50
Percentage of total sample investment accounted for by spikes	70	74
Number of investment spikes and the percentage of farms in each group		
1–2	84	80
3–4	13	18
5–6	3	2

As regards cereal farms, 51% of farms covered in the analysis present investment spikes and such observations account for 70% of the total investments. A similar tendency is revealed in dairy farms. This indicates investment decisions have been similarly affected in both cereal and dairy farms after the introduction of the CAP support. *Table 3* also provides additional interesting information on the frequency of investment spikes. It shows the number of investment spikes over the period of 2004-2014 and the percentage of farms with a certain number of spikes. It suggests that most of the farms experienced less than two investment spikes over the sample period. The average number of spikes is slightly higher for dairy farms.

Figs. 4 and *5* present the mean pure technical inefficiency and scale inefficiency across different cereal farm size groups. In case of cereal farms without investment spikes, the small farms operate at a higher level of technical efficiency than large farms. However, farms show a tendency to increase in pure technical efficiency with farm size. The mean scale inefficiency is reciprocally related to farm size. Farms with more than 150 ha of land area show the mean scale inefficiency of 4%, while farms utilising from 10 to 20 ha of land exhibit mean scale inefficiency of 33% (in case of no investment spikes). What is more, the smallest farms show the highest scale inefficiency. This suggests the major source of scale inefficiency is operation at sub-optimal scale.

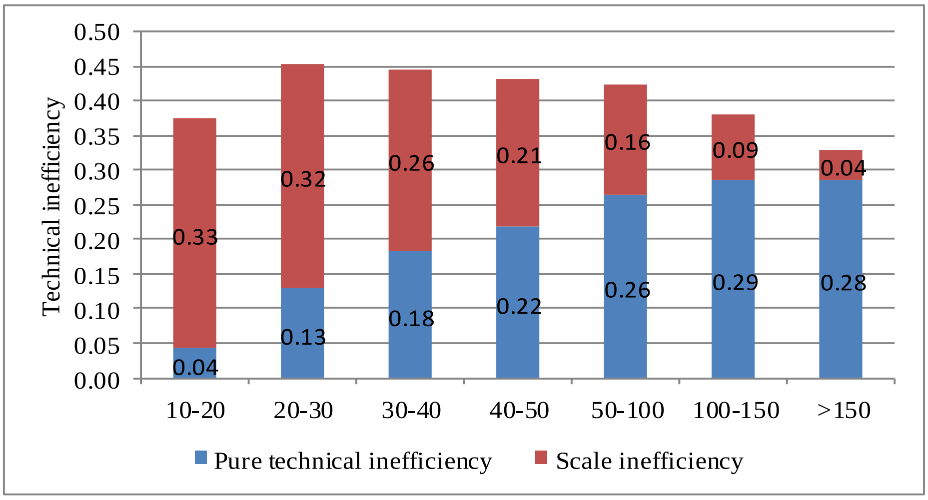

Fig. 4. Mean pure technical and scale inefficiencies for Lithuanian cereal farms without investment spikes, 2004-2014

Similar results regarding the sources of the technical efficiency were obtained for cereal farms with investment spikes. As can be seen from *Fig. 5*, the small and middle-sized farms show similar level of technical efficiency if compared to the large farms. A more detailed analysis of changes in pure technical inefficiency across the farms with and without investment spikes showed that farms with 20-50 ha exhibited the highest increase in technical efficiency. The mean scale inefficiency decreased with farm size, i.e. small farms appeared less scale efficient than large farms.

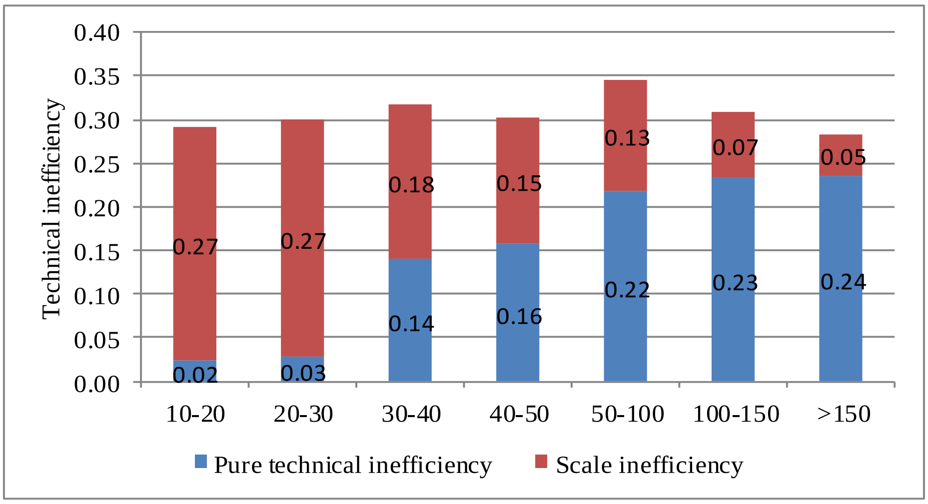

Fig. 5. Mean pure technical and scale inefficiencies for Lithuanian cereal farms with investment spikes, 2004-2014

All in all, it can be observed that the highest differences in mean scale efficiency across the cereal farms with and without investment spikes are observed for the smallest farms (less than 30 ha). For this farm size, farms with investment spikes showed 5 p.p. to 8 p.p. lower mean scale inefficiency if opposed to respective farms without investment spikes depending on the farm size group. However, larger farms enjoyed higher reduction in the pure technical inefficiency. Specifically, the smallest farms (less than 30 ha) showed the highest difference in the mean pure technical inefficiency across farms with and without investment spikes of 4 p.p., while these differences where 4 p.p. to 6 p.p. for larger farms depending on the farm size group. Note that positive numbers indicate lower inefficiency for farms with investment spikes if opposed to those without spikes in this case.

Fig. 6 and *7* present the mean pure technical inefficiency and scale inefficiency across different dairy farm size groups. In case of dairy farms without investment spikes (*Fig. 6*), the middle-size farms appear as those exhibiting the highest technical inefficiency (technical inefficiency ranged in between 29% and 31%). The pure technical inefficiency tends to increase with size for small farms (below 40 ha), whereas a slight decrease is observed for the largest farms. The scale inefficiency decreased with farm size for all size groups.

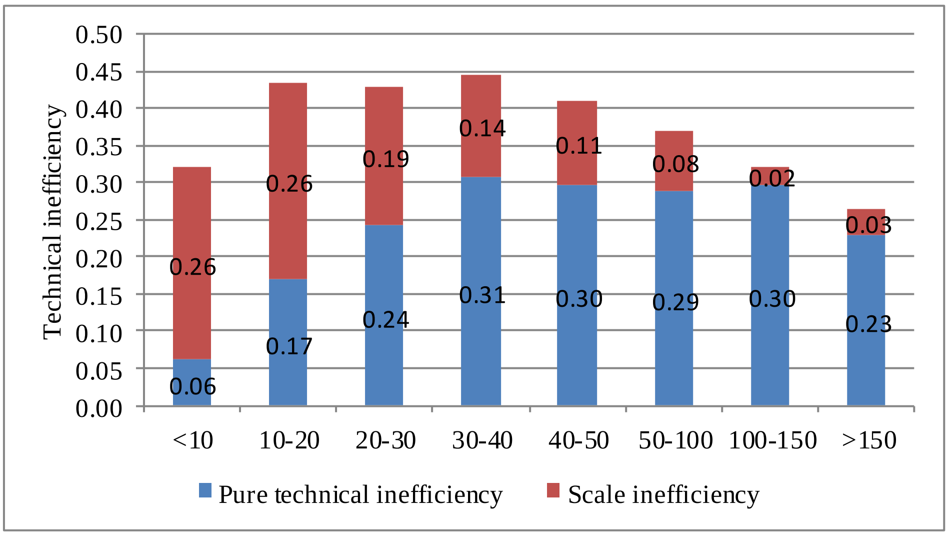

Fig. 6. Mean pure technical and scale inefficiencies for Lithuanian dairy farms without investment spikes, 2004-2014

As can be seen from *Fig. 7*, tendencies of mean inefficiencies for dairy farms with investment spikes were highly similar to those for dairy farms without investment spikes. The pure technical inefficiency appeared to be increasing with farm size, whereas the scale inefficiency followed a reciprocal relation. In general, the technical efficiency increased with farm size.

Comparison of the dairy farms with and without investment spikes reveals different sources of gains in the technical efficiency for smaller (less than 30 ha) and larger farms. Similarly to the case of cereal farms, the smaller (less than 30 ha) dairy farms with investment spikes showed lower mean scale inefficiency than the corresponding groups of dairy farms without investment spikes (the difference of 5 p.p. to 9 p.p. depending on the farm size group). The differences for larger farms were 2 p.p. at most. The opposite pattern, though, is observed for the pure technical inefficiency. In this case, larger farms showed a decrease of 6 p.p. to 11 p.p. in the pure technical inefficiency, whereas the mall farms (less than 30 ha) showed the value of 7 p.p. at most.

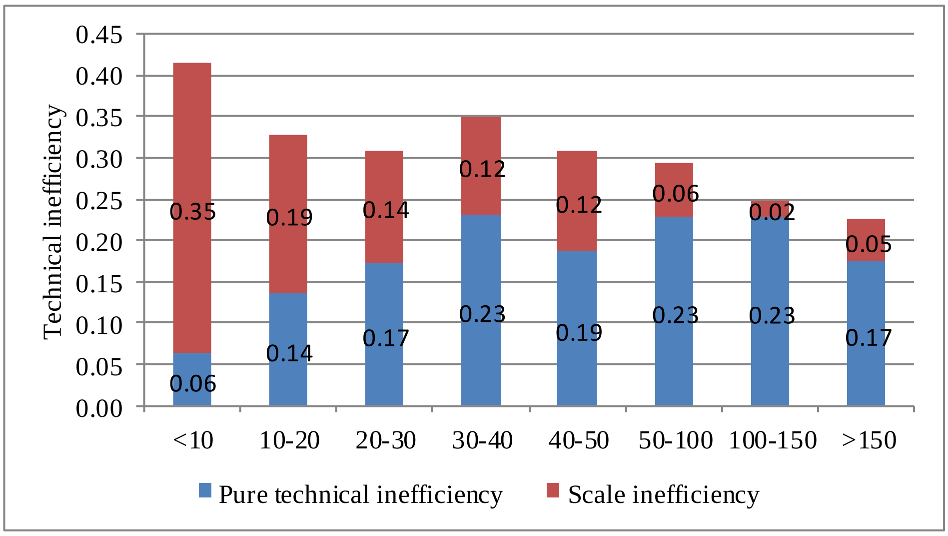

Fig. 7. Mean pure technical and scale inefficiencies for Lithuanian dairy farms with investment spikes, 2004-2014

Compared to the cereal farms, larger dairy farms remained more efficient in spite of the presence of the investment spikes. Therefore, investment spikes in cereal farms are associated with farm homogeneity in terms of technical efficiency, whereas the latter relationship is not that evident in the case of dairy farms. What is more, the smallest dairy farms showed even higher technical inefficiency in the presence of investment spikes, which indicates that excessive investments might be a more topical issue there.

Further on, we specified three different types of scale behavior. As it was already said, according to R. Färe *et al.* (1983), R. Färe and S. Grosskopf (1985), and S. Grosskopf (1986), these are increasing returns to scale (i.e., sub-optimal scale), constant returns to scale (optimal scale), and decreasing returns to scale (supra-optimal scale). The following figures present the results.

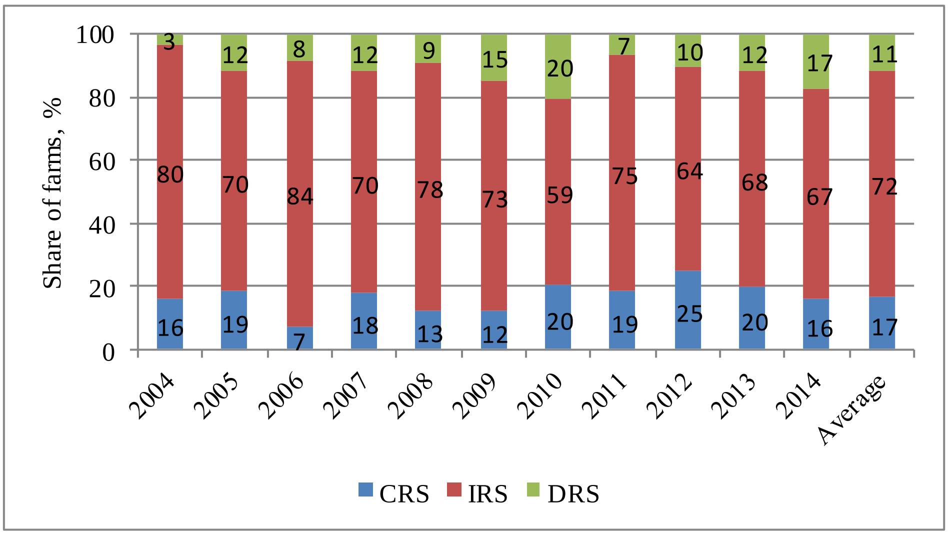

Fig. 8. The structure of Lithuanian cereal farms without investment spikes in terms of RTS, 2004-2014

As can be seen from *Fig. 8*, most of cereal farms without investment spikes operate under IRS (the share of IRS observations ranged in between 59% and 84% during the period of 2004-2014). This suggests these farms may be able to increase the productivity of their inputs by increasing farm size. The results also indicate that there are a smaller number of farms that could increase their productivity by reducing their size (the share of DRS observations amounted to 3-20% during 2004-2014). The share of CRS observations fluctuated in between 7% and 25% during the research period.

However, different farm structure can be observed for the sub-periods of 2004-2010 and 2010-2014. The mean share of IRS observations was 74% during 2004-2010, whereas it dropped to 69% during the second sub-period. The mean shares of CRS observations for the two sub-periods were 15% and 20%, respectively. However, the mean shares of DRS were the same across the two sub-periods.

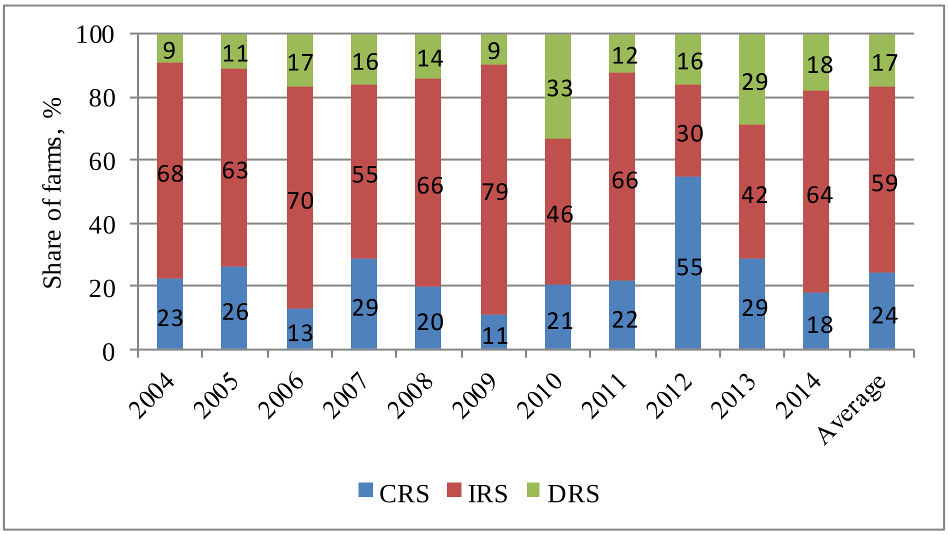

Fig. 9. The structure of Lithuanian cereal farms with investment spikes in terms of RTS, 2004-2014

In case of cereal farms with investment spikes, the mean share of CRS observations was 24% during the period of 2004-2014. This indicates that these farms operate at their optimum size and hence that the productivity of inputs cannot be improved by either increasing or decreasing the size of the farm. The mean shares of IRS observations and DRS observations were 59% and 17%, respectively, for the whole research period.

As one can note, the farm structure became more similar to the optimal one after 2010. Specifically, the mean share of IRS observations was 64% during 2004-2010, while it decreased to 50% in 2010-2014. The mean share of CRS observations was 20% during the first sub-period, but it increased up to 31% in the second one. The mean shares of IRS observations for the two sub-periods were 16% and 19%, respectively.

Dairy farms without investment spikes showed lower shares of CRS observations if opposed to the cereal farms (*Fig. 10*). This share ranged in between 5% and 19% during 2004-2014. The share of farms operating below their optimal scale fluctuated in between 65% and 84% during the research period. The share of DRS observations was the lowest one if compared to other regions of RTS and amounted to 4-15%. However, it should be noted that the share of IRS observations decreased during the period of 2004-2014, whereas the shares of CRS observations and DRS observations showed an increasing trend during the said period.

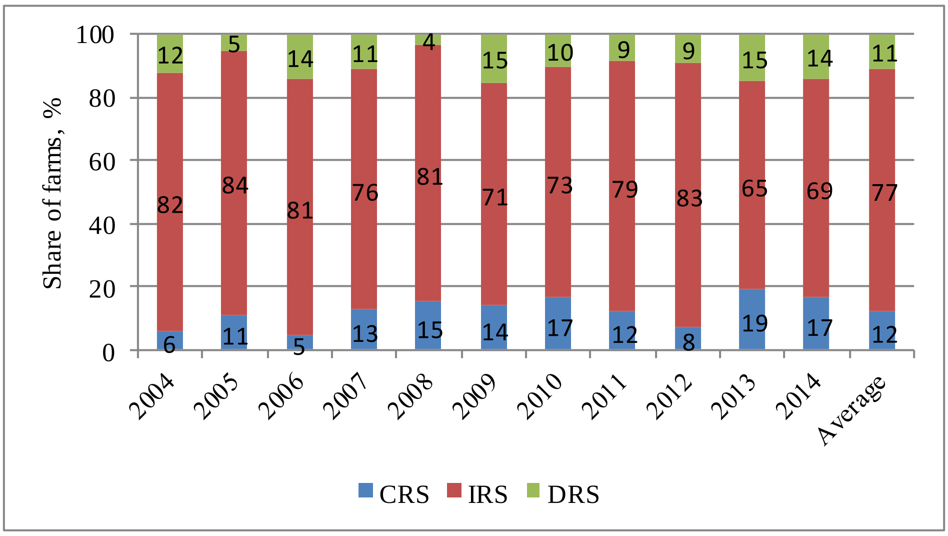

Fig. 10. The structure of Lithuanian dairy farms without investment spikes in terms of RTS, 2004-2014

Fig. 11 presents the structure of dairy farms with investment spikes. In this case, the mean share of CRS observations was 20% during 2004-2014, while the rest of the farms operated below or above optimal scale. This indicates that more dairy farms operated at the optimal scale size in case of the investment spikes.

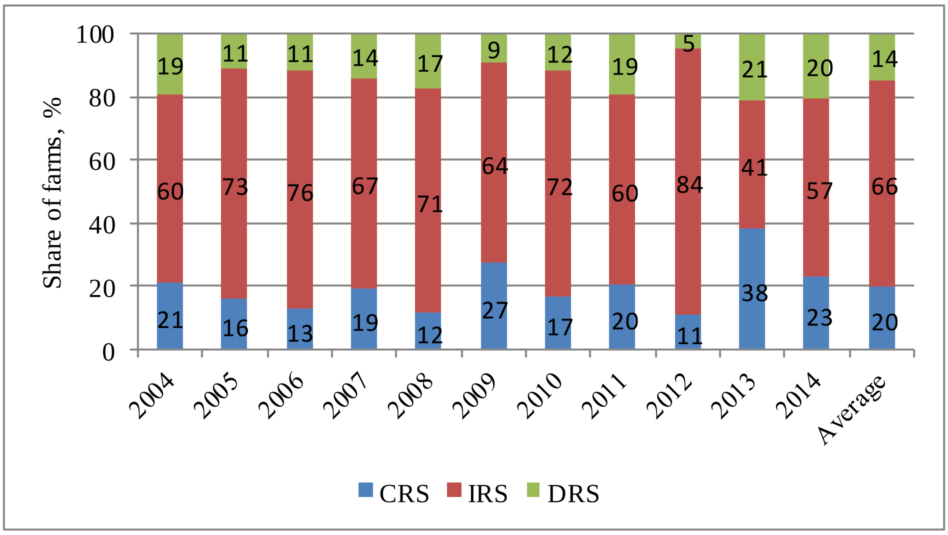

Fig. 11. The structure of Lithuanian dairy farms with investment spikes in terms of RTS, 2004-2014

A more detailed analysis showed that structure of these farms changed after 2010. The mean shares of CRS observations for the sub-periods of 2004-2010 and 2010-2014 were 18% and 23%, respectively. The mean share of IRS observations was 69% in the first sub-period, but it dropped to 61% in the second sub-period. The share of farms operating above optimal scale was 13% for the period of 2004-2010 and 16% for 2010-2014.

Conclusions

1. The results showed the support payments under the EU policies enabled Lithuanian farmers actively invest in modernization of agricultural holdings. Farms with investment spikes constituted around the half of the investigated farms. Furthermore, these investments accounted for a rather high share of overall investments in the sample (70% and 74% for cereal and dairy farms, respectively).

2. The patterns of inefficiencies for farms without investment spikes were almost identical to those for farms with investment spikes. In case of cereal farms, the small farms appeared as those exhibiting the highest level of technical efficiency, while large farms were the least efficient. The results of dairy farms were somewhat different. The small farms remained the most technically efficient farms; however, the middle-sized farms were the least efficient. In all cases the inefficiency of scale was inversely related to farm size. Both cereal and dairy farms showed lower inefficiency in the presence of investment spikes, which indicates improvements in productivity due to investments.

3. In all cases, most of farms operated below the optimal scale. The farms operating in the region of increasing returns to scale could increase productivity by increasing their input and investments. However, it is important to avoid excessive investments by maintaining the balance between output growth and investments. One possible solution for reducing technical and scale inefficiency of Lithuanian cereal and dairy farms is to find a balance between supporting small and large farms.

References

Baležentis, T. (2016). Dynamic efficiency in Lithuanian cereal farms. *Management Theory and Studies for Rural Business and Infrastructure Development*, *38*(2), 114-127.

Bilan, Y., & Strielkowski, W. (2015). Psychological decisions of polish rural entrepreneurs: daily targeting versus intertemporal substitution. *Drivers for Progress in the Global Society*, 123-128.

European Commission (2016). *FADN Public Database,* http://ec.europa.eu/agriculture/rica/database/database_en.cfm (2016 07 20).

Färe, R., Grosskopf, S. (1985). A nonparametric cost approach to scale efficiency. *The Scandinavian Journal of Economics*, *87*(4), 594-604.

Färe, R., Grosskopf, S., Lovell, C. A. K. (1983). The structure of technical efficiency. *The Scandinavian Journal of Economics*, *85*(2), 181-190.

Geylani, P. C., Stefanou, S. E. (2013). Linking investment spikes and productivity growth. *Empirical Economics*, *45*(1), 157-178.

Grosskopf, S. (1986). The role of the reference technology in measuring productive efficiency. *The Economic Journal*, *96*(382), 499-513.

Huggett, M., Ospina, S. (2001). Does productivity growth fall after the adoption of new technology? *Journal of Monetary Economics*, *48*(1), 173-195.

Janda, K., Rausser, G., & Strielkowski, W. (2013). Determinants of Profitability of Polish Rural Micro-Enterprises at the Time of EU Accession. *Eastern European Countryside,* 19, 177-217. doi: https://doi.org/10.2478/eec-2013-0009

Kapelko, M., Oude Lansink, A. (2017). Dynamic multi-directional inefficiency analysis of European dairy manufacturing firms. *European Journal of Operational Research*, *257*(1), 338-344.

Kapelko, M., Oude Lansink, A., Stefanou, S. (2016b). Assessing the Impact of Changing Economic Environment on Productivity Growth: The Case of the Spanish Dairy

Processing Industry. *Journal of Food Products Marketing*, 1-14. DOI:10.1080/10454446.2014.1000448

Kapelko, M., Oude Lansink, A., Stefanou, S. E. (2016a). Input-Specific Dynamic Productivity Change: Measurement and Application to European Dairy Manufacturing Firms. *Journal of Agricultural Economics*. DOI: 10.1111/1477-9552.12188

Kapelko, M., Oude Lansink, A., Stefanou, S. E. (2015). Analyzing the impact of investment spikes on dynamic productivity growth, *Omega*, 54, 116-124.

Krylovas, A., Zavadskas, E. K., & Kosareva, N. (2016). Multiple criteria decision-making KEMIRA-M method for solution of location alternatives. *Economic research – Ekonomska istraživanja*, *29*(1), 50-65.

Melnikienė, R. (ed.) (2016). *Lietuvos žemės ir maisto ūkis 2015 = Agriculture and food sector in Lithuania 2015*. Lietuvos agrarinės ekonomikos institutas.

Mikócziová, J. (2010). Sources of investment finance in firms in Slovakia. *Journal of Competitiveness*, *2*(1), 67-73.

Power, L. (1998). The missing link: technology, investment, and productivity. *Review of Economics and Statistics*, *80*(2), 300-313.

Rungsuriyawiboon, S., Hockmann, H. (2015). Adjustment costs and efficiency in Polish agriculture: a dynamic efficiency approach. *Journal of Productivity Analysis*, *44*(1), 51-68.

Sakellaris, P. (2004). Patterns of plant adjustment. *Journal of Monetary Economics*, *51*(2), 425-450.

Serra, T., Lansink, A. O., Stefanou, S. E. (2011). Measurement of dynamic efficiency: A directional distance function parametric approach. *American Journal of Agricultural Economics*, *93*(3), 752-763.

Silva, E., Lansink, A. O., Stefanou, S. E. (2015). The adjustment-cost model of the firm: Duality and productive efficiency. *International Journal of Production Economics*, 168, 245-256.

Simionescu, M. (2016). The relation between economic growth and foreign direct investment during the economic crisis in the European Union. *Zbornik radova Ekonomskog fakulteta u Rijeci: časopis za ekonomsku teoriju i praksu*, *34*(1), 187-213.

Statistics Lithuania (2016). *Official Statistics Portal*, http://osp.stat.gov.lt/ (2016 08).