Aggregate Efficiency Dynamics in Lithuanian Dairy Farms

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Abstract

In this paper, we attempt to identify the major groups of decision making units (dairy farms) contributing to the aggregate efficiency change. We also suggest identifying influential peers in order to gain more insights into possible development strategies within a sector. The empirical application focuses on specialist dairy farms in Lithuania. The farm-level data cover the period 2004-2016. The results indicate the presence of structural changes and resulting shifts in the aggregate efficiency. Based on the results of decomposition of the covariance term and identification of the influential peers, two models can be followed by Lithuanian dairy farms, namely "pure" family farms with lower operational scale and large farms involving hired labour.

Keywords

data envelopment analysis; aggregate efficiency; dairy farm; Lithuania

1 Introduction

Dairying is an important farming activity in Western and Northern Europe. However, increasing competition in global food markets induces uncertainties in the domestic milk market. In order to withstand these buffeting processes, dairy farms need to continuously increase their productivity. Accordingly, studies by SIPILÄINEN et al. (2014), LATRUFFE et al. (2017), SKEVAS et al. (2018a) and SKEVAS (2020), among others, investigated the dynamics and sources of efficiency and productivity in European dairy farms. KUIPERS et al. (2017) analysed patterns of entrepreneurship abilities in European dairy farms. As is the case in any other farming type, dairy farming might experience gains or losses in efficiency depending on changes in the scale of operation (LØYLAND and RINGSTAD, 2001; DONG et al., 2016; DERVILLÉ et al., 2017), among other factors. However, analysis of the relationship between farm size and efficiency was usually confined to regression-based methods, which, in the earlier literature, showed expected levels of efficiency for a given farm size. Focusing on farm size structure, any structural change is likely to affect the scale of operation. Therefore, tracking the impacts of restructuring of the sector is an important avenue for economic research.

The Lithuanian dairying sector has faced important changes in several directions, which largely correspond to those observed in the other Central and Eastern European countries (VERHEES et al., 2018; ZAKOVA KROUPOVA, 2016; STANCIU et al., 2019). Admission to the European Union (EU) in 2004 coincided with increasing support for livestock farming, yet the intensity of support has in general been higher for crop farms due to the Single Area Payment Scheme. The phasing-out of small dairy farms has been continuing due to their relatively low profitability and relatively high labour requirement per output (when compared to other types of farming).

Lithuanian dairy farms are in general smaller and less profitable than the EU average. As of 2016, the herd size of an average commercial dairy farm was 15.5 livestock units (LSU), whereas the corresponding figure for the EU was 47.7 LSU (EUROPEAN COMMISSION, 2018). The net value added per family work unit was just 4.6 thousand Eur compared to 21 thousand Eur for the EU (EUROPEAN COMMISSION, 2018). Even though milk yields have increased in Lithuania, the average yield stood at 5,604 kg/cow (EU average was 6,811 kg/cow in 2016). Therefore, dairy farming in Lithuania requires further adjustments in terms of operational scale, marketing and farming practices, among other issues. Up to now, structural change to Lithuanian farms has been directed towards increases in farm size. Following accession to the EU, public support and increasing opportunity costs contributed to intensification and mechanisation of Lithuanian dairy farms. Milk prices, too, have been differentiated across farm size groups, which further accelerated structural change. All in all, Lithuanian dairy farms present an interesting case for analysis of post-communist transition in the dairy sector under the

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effects of the Common Agricultural Policy (CAP) of the EU. The performance gaps between the EU and Lithuania indicate the need for further structural change in the sector to ensure economic viability. Identification of business model strategies is important in this regard. The use of farm-level data allows one to identify the peer farms (and, thus, the business models to follow) without restrictive a priori assumptions on the underlying technology.

The paper addresses two interrelated issues. First, we investigate the dynamics in aggregate efficiency in Lithuanian dairy farms to ascertain whether these farms have become more homogenous in terms of their efficiency. Second, we decompose the reallocation effect in the OLLEY and PAKES (1996) decomposition, along the lines suggested by KARAGIANNIS and PALEOLOGOU (2018), so that the groups of farms contributing to the different types of relationships between farm size and performance are identified. Farm performance is represented by the technical efficiency indicator, which is an integrated measure of resource utilization. This approach allows identifying and describing the best performing farms based on the underlying productive technology.

Measurement of the aggregate efficiency is useful to quantify the gains (or losses) in the sector-level productivity due to re-structuring (as represented by the reallocation effect) and actual efficiency gains at the firm level (as represented by the average efficiency). Given the two components of aggregate efficiency, the changes in it can be due to the reallocation effect if–production is concentrated into production units associated with different levels of technical efficiency besides the conventionally measured changes in average technical efficiency. For these purposes, farm-level data from the Farm Accountancy Data Network (FADN) are applied. The data cover the period of 2004-2016. Data envelopment analysis (DEA) is used to calculate the technical efficiency measures.

This paper presents a frontier-based framework for analysing the performance of Lithuanian dairy farms without arbitrarily chosen grouping schemes. The mean values of farm size and efficiency levels are used as thresholds to identify relatively small and big farms as well as relatively low- and high-efficiency farms. The importance of these groups of farms on the aggregate efficiency and its dynamics are then assessed by exploiting the decomposition of the covariance term.

The paper proceeds as follows: Section 2 presents the key concepts and techniques used in the paper (aggregate technical efficiency, Olley-Pakes decomposition, identification of the most influential farms). Section 3 focuses on the data used. Section 4 gives the results. The results are discussed in Section 5. Finally, conclusions are presented in Section 6.

2 Methods

2.1 Productive Technology and Efficiency

The measures of efficiency are based on the non-parametric DEA approach. In other words, we constructed an empirical non-parametric frontier involving a deterministic measurement of efficiency. The productive technology is defined as

$$T=\left\{(x,y)\mid x \text{ can produce } y\right\}, \tag{1}$$

where $x \in R_{+}^{m}$ is a vector of input quantities and $y \in R_{+}^{n}$ is a vector of output quantities. The DEA (CHARNES et al., 1978; BANKER et al., 1984) relies on a piece-wise linear production frontier going through the most productive empirical observations. Let there be K decision-making units (DMUs) indexed over $k=1,2,\ldots,K$. Assuming constant returns to scale (CRS), one arrives at a convex cone:

$$\hat{T}_{DEA}^{CRS}=\left\{\begin{array}{l}(x,y)\mid \sum_{k=1}^{K}\lambda_k x^k \le x, \sum_{k=1}^{K}\lambda_k y^k \ge y,\\ \lambda_k \ge 0, k=1,2,\ldots,K\end{array}\right\}, \tag{2}$$

where λ_k are intensity variables representing the importance of different DMUs for the observations under evaluation. The convex hull defines the variable returns to scale (VRS) technology which is obtained by imposing $\sum_{k=1}^{K}\lambda_k=1$ on the CRS technology in Eq. 2. Finally, non-increasing returns to scale (NIRS) technology is obtained by supplementing Eq. 2 with $\sum_{k=1}^{K}\lambda_k \le 1$.

The output-oriented efficiency measures seek to adjust the output vector in order to approach the boundary of the production possibility set. In this paper, we apply the output distance function (SHEPHARD, 1953):

$$D_O(x,y)=\left(\min \phi \,\middle|\, \left(x,\frac{y}{\phi}\right)\in T\right), \tag{3}$$

where $\phi \in (0,1]$. Note that $\phi = 1$ indicates full efficiency. DEA can be applied to estimate the distance function. Taking any DMU k_0 and assuming CRS technology, the DEA problem is

$$\phi_{k_0}^{CRS} = \min\left\{\phi \left| \begin{array}{l} \sum_{k=1}^{K} \lambda_k x_i^k \leq x_i^{k_0}, i = 1,2,...,m; \\ \sum_{k=1}^{K} \lambda_k y_j^k \geq \dfrac{y_j^{k_0}}{\phi}, j = 1,2,...,n; \\ \lambda_k \geq 0, k = 1,2,...,K \end{array} \right.\right\}. \quad (4)$$

Analogously, the VRS or NIRS measures can be implemented by appending Eq. 4 with constraints on the intensity variables as was discussed above. Following FÄRE and GROSSKOPF (1985), efficiency scores related to different combinations of the returns to scale allow one to identify the returns to scale prevailing for a certain observation. Specifically, a DMU operating at sub-optimal scale size (i.e. in the region of IRS) shows $\phi^{NIRS} = \phi^{CRS} < \phi^{VRS}$. A DMU operating at the most productive scale size is associated with $\phi^{CRS} = \phi^{VRS}$. Finally, a DMU operating at a supra-optimal scale size (i.e. in the region of DRS) exhibits $\phi^{CRS} < \phi^{VRS} = \phi^{NIRS}$.

2.2 Aggregate Efficiency and the Olley-Pakes Decomposition

The measures of efficiency can be aggregated in the manner of FÄRE and KARAGIANNIS (2017). As long as the efficiency scores are based on Eq. 4, they are defined as the ratio of the observed output quantity over the optimal one (in the case of a single output). Therefore, the rule of denominator (FÄRE and KARAGIANNIS, 2017) suggests that the optimal output quantities should be used as the weighting factors to aggregate the efficiency scores. As we assume VRS technology, the aggregate efficiency is calculated as:

$$\phi = \frac{\sum_{k=1}^{K}\left(y^k / \phi_k^{VRS}\right)\phi_k^{VRS}}{\sum_{k=1}^{K}\left(y^k / \phi_k^{VRS}\right)} = \frac{\sum_{k=1}^{K} y^k}{\sum_{k=1}^{K} y^{k,*}}, \quad (5)$$

where $y^{k,*}$ is the optimal output quantity for DMU k. In the case of a multiple-output setting, the use of revenue shares would be applied for aggregation across the outputs.

Farms vary in their importance (size) and performance (efficiency). These characteristics may also vary across time for a given farm. Therefore, the gains (resp. losses) in aggregate efficiency can be achieved through increases (resp. decreases) in farm-level efficiency affecting the average efficiency and changes in the relative importance of the farms. In the event that relatively more efficient (resp. less efficient) farms expand their scale size, the aggregate efficiency increases (resp. decreases). The public policy measures (support payments, environmental regulations) and market structure may affect the average and aggregate efficiency, as less efficient farms may continue to operate or adjust their operational scale (see, e.g. LATRUFFE et al., 2017, and MINVIEL and LATRUFFE, 2017 for discussion on the impacts of support payments on agricultural efficiency). In order to identify the sources of contributions towards the aggregate efficiency (and, especially, to the covariance term), the aggregate efficiency can be decomposed (see KARAGIANNIS, 2015) in the manner of OLLEY and PAKES (1996) as follows:

$$\begin{aligned} \phi &= \sum_{k=1}^{K} \theta_k \phi_k^{VRS} = \bar{\phi} + \sum_{k=1}^{K}\left(\theta_k - \bar{\theta}\right)\left(\phi_k^{VRS} - \bar{\phi}\right) \\ &= \bar{\phi} + \sum_{k=1}^{K} \tilde{\theta}_k \tilde{\phi}_k^{VRS} \end{aligned}, \quad (6)$$

where $\bar{\phi}$ is the average efficiency, θ_k is the farm share in terms of potential output in our case, and $\bar{\theta}$ is the average farm share; variables with tildes denote values centred around respective means. Therefore, the aggregate efficiency can be decomposed into the average efficiency and the reallocation effect depicted by the covariance term. The latter can be further decomposed (see KARAGIANNIS and PALEOLOGOU, 2018) with respect to different combinations of farm size and efficiency taking the average values as reference:

$$\begin{aligned} \sum_{k=1}^{K} \tilde{\theta}_k \tilde{\phi}_k^{VRS} = & \sum_{\substack{\tilde{\theta}_k < 0 \\ \tilde{\phi}_k^{VRS} < 0}} \tilde{\theta}_k \tilde{\phi}_k^{VRS} + \sum_{\substack{\tilde{\theta}_k < 0 \\ \tilde{\phi}_k^{VRS} = 0}} \tilde{\theta}_k \tilde{\phi}_k^{VRS} + \sum_{\substack{\tilde{\theta}_k < 0 \\ \tilde{\phi}_k^{VRS} > 0}} \tilde{\theta}_k \tilde{\phi}_k^{VRS} \\ & + \sum_{\substack{\tilde{\theta}_k = 0 \\ \tilde{\phi}_k^{VRS} < 0}} \tilde{\theta}_k \tilde{\phi}_k^{VRS} + \sum_{\substack{\tilde{\theta}_k = 0 \\ \tilde{\phi}_k^{VRS} = 0}} \tilde{\theta}_k \tilde{\phi}_k^{VRS} + \sum_{\substack{\tilde{\theta}_k = 0 \\ \tilde{\phi}_k^{VRS} > 0}} \tilde{\theta}_k \tilde{\phi}_k^{VRS} \\ & + \sum_{\substack{\tilde{\theta}_k > 0 \\ \tilde{\phi}_k^{VRS} < 0}} \tilde{\theta}_k \tilde{\phi}_k^{VRS} + \sum_{\substack{\tilde{\theta}_k > 0 \\ \tilde{\phi}_k^{VRS} = 0}} \tilde{\theta}_k \tilde{\phi}_k^{VRS} + \sum_{\substack{\tilde{\theta}_k > 0 \\ \tilde{\phi}_k^{VRS} > 0}} \tilde{\theta}_k \tilde{\phi}_k^{VRS} \end{aligned} \quad (7)$$

As one can note, the second, fourth to sixth and eighth terms in the right-hand side of Eq. 7 equal zero and do not affect the magnitude of the covariance term. The positive contribution towards the covariance term comes from the first and ninth components, i.e. in cases where relatively small (resp. large) farms show a relatively low (resp. high) level of efficiency. Therefore, analysis of the covariance term allows identifying the exact sources of changes in the aggregate efficiency due to changes in relative farm size and relative efficiency. Note that the equations presented above do not include a time index, yet they can be applied for each time period independently.

2.3 Influential Observations

In order to identify the most influential observations, we consider the four indicators for each efficient observation. *First*, the number of times a certain efficient farm acts as a peer for inefficient farms represents the number of farms in the region of the production possibility set dominated by the efficient farm. *Second*, the number of times an efficient farm is assigned the highest value of the intensity variable (weight) indicates the degree to which an efficient farm dominates over the other efficient farm(s) in the region of the production possibility set. *Third*, the reference share (TORGENSEN et al., 1996) is defined as the share of the output gap that is due to a particular efficient farm:

$$\rho^{k^*} = \frac{\sum_{k=1}^{K} \lambda_{k^*}^{k} \left(\hat{y}^{k} - y^{k} \right)}{\sum_{k=1}^{K} \hat{y}^{k} - \sum_{k=1}^{K} y^{k}}, \tag{8}$$

where $k^* \in (1,2,\ldots,K)$ is the index of an efficient farm and $\hat{y}^k$ and y^k denote the efficient and actual levels of output for the k-th farm, respectively; and $\lambda_{k^*}^{k}$ is the solution of Eq. 6 for the k-th farm. *Fourth*, the benchmarking share (JOHNSON and ZHU, 2003) represents the average impact of a certain efficient farm over the inefficient ones without considering the level of output:

$$\rho^{k^*} = \frac{\sum_{k=1}^{K} \lambda_{k^*}^{k}}{\#\left(\phi_k < 1\right)}, \tag{9}$$

where the denominator returns the number of inefficient observations. The four indicators are normalized by their maximum values and summed, thus assuming equal importance thereof. The resulting composite indicator then defines the relative influence of each efficient farm. Most importantly, this approach allows one to capture the self-evaluator farms in the analysis. Then, the role of these influential/peer farms in the elements of the covariance term will be considered.

3 Data Description

The empirical analysis is based on the FADN data for Lithuanian specialist dairy farms. The productive technology is modelled by considering four inputs, namely labour, herd size, intermediate consumption and capital assets. Labour is measured in hours worked and includes both family and hired labour. Herd size is measured in livestock units (LSU). Intermediate consumption includes specific costs (feed, veterinary expenses etc.) and overheads. Capital assets include the value of machinery and buildings. A single output is considered, i.e. total output which includes crop, livestock and other outputs. Intermediate consumption, capital assets and output are measured in monetary terms (Euro). The technology is defined for each time period independently. As we are more interested in the distribution of the farms according to their efficiency levels within each sub-period, we do not apply deflation.

Lithuania did not exceed its national milk production quota that existed in the EU until 2014. Therefore, we do not include this variable into the production model and implicitly assume that the quota was equally productive across the farms in the sample. We also do not include the CAP payments into the production technology. Indeed, it could enter into the analysis as a correlate of efficiency (MINVIEL and LATRUFFE, 2017) rather than an input or output. In Lithuania, dairy farms received direct coupled payments for milk until 2007, and then coupled payments were introduced that were linked to the number of cows.

In our setting, we use a single output expressed in monetary terms. By doing so, we essentially measure the revenue efficiency which is assumed to correspond to technical efficiency assuming the output prices are uniform across the observations. Also, this leads to an implicit assumption that the output price ratios are fixed over time when analysing the results longitudinally. A more detailed setting could aim at measuring the technical efficiency in a multi-output perspective. However, that would pose difficulties in calculating the aggregate efficiency.

The super-efficiency DEA (ANDERSEN and PEDERSEN, 1993) was applied to identify the outliers. In essence, this technique sets the intensity variable associated with the observation under evaluation equal to zero. Specifically, we allowed for 20% super-efficiency. Observations exceeding this limit were treated as outliers. As a result, 7.5% of observations were removed each year on average.

The descriptives for the dataset after removing the outliers are presented in Table 1. In general, input and output quantities increased over time, indicating the presence of restructuring of Lithuanian dairy farms, i.e. average farm size increased (both in real and nominal terms). The rates of growth, however, varied across the input/output variables. More specifically, the assets showed the steepest increase in nominal terms (from 43.8 thousand Euro in 2004 up to 115.1 thousand Euro in 2016) and real terms (from 35.2 thousand Euro up to 76.3 thousand Eur). This is obviously related to farm modernisation and expansion due to support payments under the CAP. The intermediate consumption also showed vibrant growth with an increase from 26.3 thousand Euro up to 61.7 thousand Euro during 2004-2016 (in nominal terms). This also indicates that Lithuanian dairy farming has become more intensive, because the herd size increased at much lower pace than intermediate consumption did.

There have been fluctuations in labour and herd size during the period covered. Among other factors, these can be explained by changes in incentives to embark on dairy farming. Indeed, these incentives were affected by shocks in milk prices and the resulting "price scissors". For instance, abolition of the milk quota in the EU led to volatility of the milk market with corresponding corrections in production decisions in 2015-2016 (THORSØE et al., 2020).

The differences in the rates of growth associated with different inputs indicate the changes in the underlying farming practices as the input-mix structure was

Table 1. Descriptive statistics for inputs and outputs describing performance of Lithuanian dairy farms, 2004-2016

Year	Labour, hours	Herd size, LSU	Intermediate consumption, Euro	Assets, Euro	Output, Euro	Intermediate consumption, Euro*	Assets, Euro*	Output, Euro*
Average								
2004	5,071	48.4	26,338	43,807	50,049	34,429	35,243	64,001
2005	5,692	50.2	31,849	46,316	63,578	41,633	37,261	73,586
2006	5,614	51.2	34,060	64,750	64,029	41,185	39,920	73,344
2007	5,807	49.9	35,443	83,290	71,684	39,337	52,749	74,054
2008	6,292	60.1	49,250	69,850	89,538	45,142	36,725	82,752
2009	5,967	57.3	44,436	112,860	71,298	49,264	90,433	80,110
2010	6,141	59.0	48,304	120,849	87,987	48,304	120,849	87,987
2011	5,901	56.6	54,562	117,802	96,116	45,850	98,414	84,833
2012	6,097	57.7	59,934	130,456	102,277	47,454	87,908	88,782
2013	6,293	60.3	65,115	127,129	114,803	54,581	79,159	92,958
2014	6,432	66.9	73,633	125,969	118,356	63,696	90,042	106,244
2015	5,682	60.9	60,115	108,221	90,213	50,988	74,893	94,961
2016	5,678	62.1	61,687	115,093	91,774	60,007	76,322	97,736
Standard deviation								
2004	2,290	35.3	23,729	57,484	41,922	31,018	46,246	53,609
2005	3,847	42.2	29,883	59,479	62,716	39,063	47,851	72,588
2006	2,479	44.5	34,902	100,652	65,794	42,203	62,054	75,365
2007	3,366	48.7	38,576	121,790	78,505	42,815	77,131	81,100
2008	3,968	55.0	52,101	104,831	93,438	47,755	55,116	86,357
2009	3,465	58.3	50,629	143,806	82,840	56,130	115,229	93,079
2010	5,466	67.5	56,554	167,669	105,274	56,554	167,669	105,274
2011	6,099	70.2	72,712	168,467	120,418	61,103	140,741	106,282
2012	6,065	69.4	78,633	183,675	128,327	62,259	123,770	111,395
2013	6,556	70.2	83,948	176,761	150,393	70,367	110,063	121,776
2014	5,060	77.1	95,468	183,167	154,777	82,585	130,927	138,938
2015	4,428	73.1	80,415	165,142	125,462	68,206	114,285	132,065
2016	4,443	74.4	84,284	189,283	129,732	81,988	125,519	138,160

Note: outlying observations have been removed; * indicates deflated variables in Euro of 2010.
Source: designed by the authors

altered. Indeed, dairy farming has become less labour-intensive (i.e. requiring less labour force per output) throughout 2004-2016 (Figure 1). Also, as noted before, the input intensity per LSU has increased. This allows achieving higher outputs due to a yield effect rather than expansion of the scale size in terms of labour force and herd size. Therefore, there have been both expansion and intensification in Lithuanian dairy farming.

The FADN relies on a rotating sample. In our sample, there are 1,051 farms covered. The sample comprises 3,189 farm-year observations. This gives an average of 3 years per farm on the panel. By relying on the FADN sample, we implicitly assume that the changes in the sample correspond to changes in Lithuanian farm structure. Instead of choosing a smaller number of farms that forms the balanced panel appearing each year in the sample, we opted for a higher number of observations and kept to the rotating panel. Note that this may cause a bias, yet we assume that the rotation used by the FADN is reasonable.

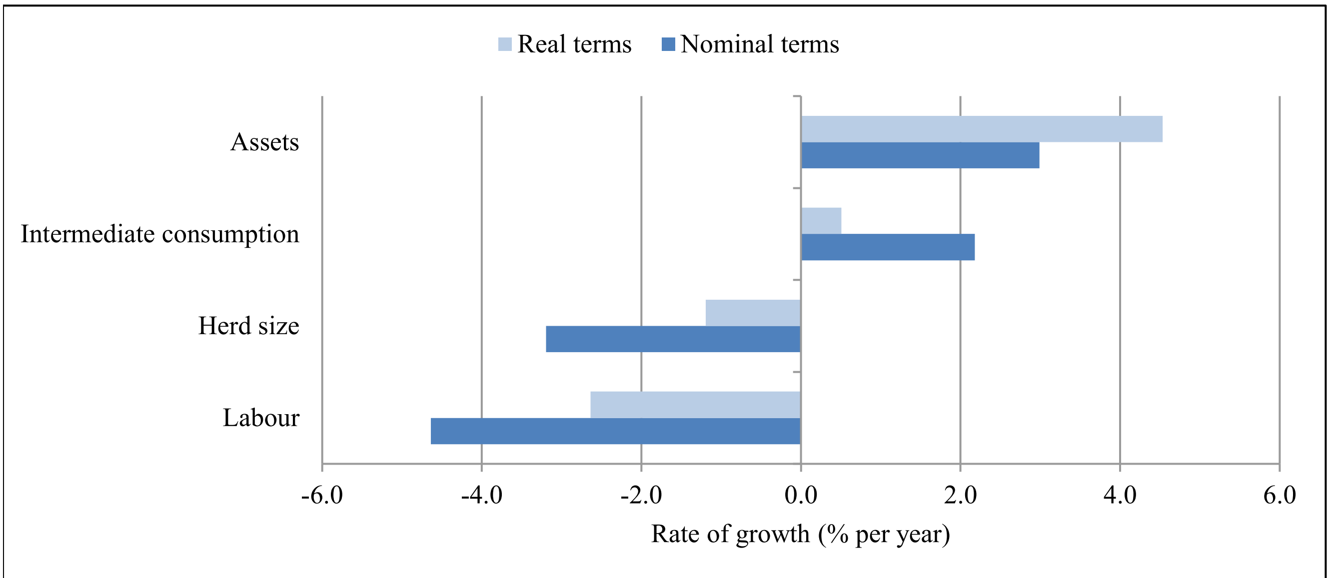
4 Empirical Results

The dynamics in technical efficiency (TE) represent changes in concentration of the farms near the production frontier (in case time sections of a panel are analysed independently). The efficiency scores considered in this study are relative to the contemporaneous frontiers. As such, they reflect the dynamics in homogeneity of farm performance rather than productivity change over time. Table 2 presents the distribution of the VRS TE scores, i.e. “pure” TE scores.

The mean TE ranged between 0.75 and 0.84 during 2004-2016. A closer look at the distribution of the efficiency scores reveals two groups of farms concentrated around two levels of the TE. The first group comprises efficient and highly efficient farms with TE scores exceeding 0.9, whereas the second group falls around the value of 0.7-0.8, depending on the time period. Therefore, Lithuanian dairy farms can be divided into the two groups in terms of efficiency level. Furthermore, Figure 2 shows that the two groups of farms approached each other during 2004-2016. This pattern can be further analysed by looking into the relationships between TE and farm size in each group. Empirically, these linkages can be tested by using the size-efficiency covariance term and its decomposition as suggested in Section 2.

The integrated measure of farm size can be obtained by considering the region of returns to scale (RTS) which a certain farm operates in. The performance of farms operating in different regions of RTS is analysed in Table 3. The differences in pure TE are not decisive across the regions of RTS. Comparing the pure TE to scale efficiency (SE) - which is the ratio of CRS and VRS TE scores - one can note that SE dominated against TE in Lithuanian dairy farms during 2004-2016. Indeed, the level of SE was rather high independently on the regions of RTS, and the minimum average value was 0.87 for the whole period covered. In general, most of the farms can be considered as operating below the most productive scale size

Figure 1. Dynamics in the input requirement per output in Lithuanian dairy farms, 2004-2016 (% per year)



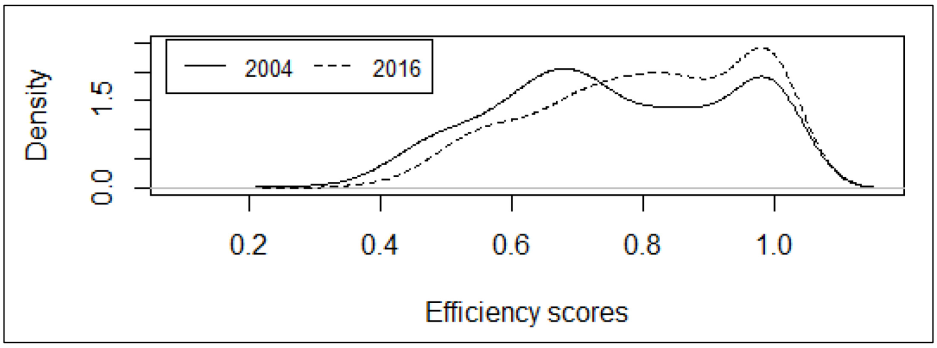
Note: input requirements are measured per 1 Euro of output as provided in Table 1; stochastic rates of growth are applied.
Source: designed by the authors

Table 2. Distribution of Lithuanian dairy farms across different levels of efficiency (VRS), 2004-2016

	Year	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Efficiency score	1	44	42	31	36	46	39	59	42	53	51	57	46	53
	(0.9, 1)	33	16	21	23	22	13	49	22	33	42	30	26	29
	(0.8, 0.9]	49	30	24	26	37	25	61	56	61	63	52	46	44
	(0.7, 0.8]	46	33	23	35	29	44	59	59	78	68	57	67	42
	(0.6, 0.7]	30	30	14	28	37	34	46	77	50	49	55	50	70
	(0.5, 0.6]	27	12	8	19	21	25	22	41	29	26	26	41	31
	(0.4, 0.5]	6	2	2	6	2	9	5	13	4	10	6	19	24
	[0.2, 0.4]	1						2			1	2	2	3
No of obs.		236	165	123	173	194	189	303	310	308	310	285	297	296
Summary statistics														
Average		0.80	0.81	0.84	0.80	0.80	0.77	0.81	0.75	0.80	0.80	0.79	0.76	0.76
Min		0.37	0.40	0.45	0.44	0.40	0.42	0.34	0.41	0.45	0.37	0.37	0.39	0.25

Source: designed by the authors

Figure 2. Kernel density plots for the efficiency scores in 2004 and 2016



Source: designed by the authors

(i.e. they operated in the region of IRS). The average share of farms operating under IRS was 62.3%, the share of farms operating under CRS (i.e. the most productive scale size) was 7.1%, and the remaining 30.7% fell under DRS. Therefore, most Lithuanian dairy farms could increase their operation scale, yet losses in productivity due to operation at sub-optimal scale are not high (a formal test for RTS of the underlying technology could be carried out by following SIMAR and WILSON, 2002).

In order to gain insights into the sector-wide performance, we further calculate the aggregate efficiency for Lithuanian dairy farms. Following the denominator rule (FÄRE and KARAGIANNIS, 2017), we apply Eq. 5 to obtain the aggregate efficiency scores (Table 4). The aggregate efficiency remained rather stable during 2004-2016. This indicates that the efficiency gap of the best-performing farms and the rest persisted over time. The average TE remained the most important contributor to the aggregate TE, yet its contribution gradually declined from 98.4% in 2004 down to 92.6% in 2016 (Table 4). Thus, the importance of the covariance term has increased, as evidenced by its contribution share increasing from 1.6% in 2004 up to 7.4% in 2016. This finding clearly indicates that structural adjustment has been taking place in the sector of Lithuanian dairy farms. This can be related to situations in the milk market and demographic transition in rural areas. The covariance term can be further analysed by factorising the contributions of different farm groups.

The covariance term is decomposed into the contributions by the different groups of farms in Table 5. The increasing disparity among the farms in terms of their size can be seen by comparing the data in Tables 1 and 5. By construction, the sums of variances for combinations of relatively small/efficient and relatively large/inefficient farms show negative signs. Obviously, the increasing average farm size was accompanied by an increasing share of relatively small farms (i.e. those below the average farm size). This indicates that the movement of the average farm size was mainly driven by steep expansion of the relatively large farms which pushed some medium-sized farms into the group of relatively small ones.

Table 3. Technical efficiency level across different regions of returns to scale (RTS) in Lithuanian dairy farms, 2004-2016

Year	RTS	Average efficiency		No of farms	Year	RTS	Average efficiency		No of farms
		VRS TE	SE				VRS TE	SE	
2004	IRS	0.79	0.90	146	2011	IRS	0.75	0.90	128
	CRS			18		CRS			18
	DRS	0.77	0.97	72		DRS	0.73	0.96	164
2005	IRS	0.79	0.87	101	2012	IRS	0.78	0.93	226
	CRS			12		CRS			19
	DRS	0.81	0.96	52		DRS	0.80	0.96	63
2006	IRS	0.82	0.88	90	2013	IRS	0.77	0.92	201
	CRS			9		CRS			20
	DRS	0.85	0.96	24		DRS	0.82	0.97	89
2007	IRS	0.79	0.90	114	2014	IRS	0.78	0.92	183
	CRS			13		CRS			25
	DRS	0.74	0.96	46		DRS	0.77	0.98	77
2008	IRS	0.77	0.90	129	2015	IRS	0.74	0.89	177
	CRS			19		CRS			19
	DRS	0.82	0.96	46		DRS	0.74	0.96	101
2009	IRS	0.77	0.89	96	2016	IRS	0.72	0.91	171
	CRS			13		CRS			20
	DRS	0.74	0.97	80		DRS	0.76	0.96	105
2010	IRS	0.79	0.91	209					
	CRS			16					
	DRS	0.82	0.96	78					

Note: IRS, CRS and DRS denote farms operating at increasing, constant and decreasing returns to scale, respectively; VRS TE and SE stand for VRS technical efficiency and scale efficiency, respectively; VRS TE and SE equal unity in the CRS region by construction.
Source: designed by the authors

The share of relatively small farms increased from 61.8% in 2004 to 68.3% in 2016. Looking at efficiency in this group of farms, one can notice that the low efficiency farms (i.e. those with lower-than-average efficiency) became prevalent (their share in the sample went up from 30.9% to 42.6%), whereas the opposite trend prevailed for the high efficiency farms (i.e. those with higher-than-average efficiency).

Table 4. Decomposition of the output efficiency for Lithuanian dairy farms, 2004-2016

Year	Aggregate TE	Average TE		Covariance term	
		Level	Contribution (%)	Level	Contribution (%)
2004	0.816	0.803	98.4	0.013	1.6
2005	0.832	0.814	97.8	0.019	2.2
2006	0.862	0.838	97.3	0.023	2.7
2007	0.817	0.795	97.3	0.022	2.7
2008	0.831	0.805	96.9	0.026	3.1
2009	0.818	0.771	94.2	0.047	5.8
2010	0.839	0.811	96.7	0.028	3.3
2011	0.803	0.752	93.8	0.050	6.2
2012	0.830	0.797	96.1	0.032	3.9
2013	0.843	0.796	94.4	0.047	5.6
2014	0.836	0.794	95.0	0.042	5.0
2015	0.802	0.756	94.2	0.046	5.8
2016	0.816	0.756	92.6	0.061	7.4

Note: contribution represents the relative contribution to the aggregate efficiency
Source: designed by the authors

Within the relatively large farm group, the share of low efficiency farms tended to decrease (the trend coefficient is -0.47 p.p.), whereas the share of highly efficient farms remained rather stable (trend coefficient is -0.09). However, the increasing component of highly efficient relatively large farms indicates a serious increase in efficiency there (again, the use of contemporaneous frontiers implies we are not able to deduce about productivity change in this case). The comparison of the farm distribution across farm size and efficiency pattern indicates that the major contribution to the covariance term came from the relatively small low efficiency farms and relatively large high efficiency farms. Moreover, the contributions to the covariance term from these two groups of farms increased over 2004-2016. This confirms that the persistence of small inefficient

Table 5. Decomposition of the covariance term with respect to farm size ($\tilde{\theta}_{kt}$) and efficiency ($\tilde{\phi}_{kt}$) level for Lithuanian dairy farms, 2004-2016

Year	$\tilde{\theta}_{kt} < 0$				$\tilde{\theta}_{kt} > 0$			
	$\tilde{\phi}_{kt} < 0$		$\tilde{\phi}_{kt} > 0$		$\tilde{\phi}_{kt} < 0$		$\tilde{\phi}_{kt} > 0$	
	Sum	**Share (%)**	**Sum**	**Share (%)**	**Sum**	**Share (%)**	**Sum**	**Share (%)**
2004	0.0166	30.9	-0.0186	30.9	-0.0123	15.7	0.0271	22.5
2005	0.0137	31.5	-0.0220	32.1	-0.0092	17.6	0.0362	18.8
2006	0.0204	29.3	-0.0244	35.0	-0.0076	15.4	0.0350	20.3
2007	0.0271	33.5	-0.0283	31.2	-0.0116	15.6	0.0347	19.7
2008	0.0259	32.5	-0.0249	30.4	-0.0113	13.9	0.0363	23.2
2009	0.0328	39.7	-0.0278	27.5	-0.0059	13.2	0.0483	19.6
2010	0.0248	33.7	-0.0276	33.0	-0.0102	13.2	0.0409	20.1
2011	0.0323	43.9	-0.0246	24.5	-0.0053	10.0	0.0477	21.6
2012	0.0288	37.7	-0.0259	29.2	-0.0113	13.6	0.0409	19.5
2013	0.0331	35.2	-0.0258	32.9	-0.0070	12.9	0.0469	19.0
2014	0.0329	37.5	-0.0267	30.9	-0.0099	11.6	0.0454	20.0
2015	0.0339	37.7	-0.0317	31.3	-0.0063	11.1	0.0506	19.9
2016	0.0410	42.6	-0.0333	25.7	-0.0061	11.5	0.0591	20.3
Trend		0.84		-0.29		-0.47		-0.09

Note: sum and Share refer to the sum of the covariance terms and the share of farms within a particular group efficiency/size combination (relative to sample size for each time period); variables with a tilde sign are centred on the means for the respective time periods.
Source: designed by the authors

farms was offset by expansion of large technically efficient ones with respect to contribution to the covariance term (and aggregate efficiency).

Yet another observation can be made by looking at the dynamics in the contributions to the covariance term. More specifically, year 2006 is associated with increased production risk due to drought. The economic crisis of 2008-2009 and a Russian embargo following 2014 induced price risk. Therefore, 2009-2011 and 2016 saw increases in the contribution to the covariance term from the relatively small low-efficiency farm group. This indicates the latter group was affected to the highest degree by the aforementioned perturbations and a direct relationship between farm size and efficiency prevailed there.

The efficient farms (in VRS technology) were located in two groups: relatively small and relatively large high-efficiency farms (Table 6). In addition to fully efficient farms, we also identify the peer farms, i.e. those acting as peers for at least one other farm. Table 6 suggests that both efficient and peer farms are present among relatively small and large farms.

As we have already identified the efficient farms in both the relatively small and large farm groups, the characteristics of these farms can be used to define the models to follow in Lithuanian dairy sectors. Based on the criteria outlined in Section 2.3, we further pick the five most influential observations within each year. These farms come from different size groups. Table 7 presents the average input-output values for influential peers, whereas Table 8 presents some additional characteristics of these farms.

The absolute values of inputs and outputs given in Table 7 suggest that two types of efficient farm models can be identified. The absolute levels of inputs and

Table 6. Distribution of the technically efficient and peer farms across different combinations of farm size/efficiency (in per cent), 2004-2016

Year	$\tilde{\theta}_{kt} < 0$		$\tilde{\theta}_{kt} > 0$	
	$\tilde{\phi}_{kt} > 0$		$\tilde{\phi}_{kt} > 0$	
	Eff.	**Peer**	**Eff.**	**Peer**
2004	59.1	54.1	40.9	45.9
2005	50.0	48.4	50.0	51.6
2006	71.0	69.2	29.0	30.8
2007	66.8	63.7	33.2	36.3
2008	56.5	52.4	43.5	47.6
2009	61.7	61.6	38.3	38.4
2010	59.5	54.8	40.5	45.2
2011	59.6	57.5	40.4	42.5
2012	69.8	65.0	30.2	35.0
2013	62.8	56.1	37.2	43.9
2014	68.5	69.2	31.5	30.8
2015	74.0	71.1	26.0	28.9
2016	71.5	66.9	28.5	33.1
Trend	1.08	1.04	-1.08	-1.04

Source: designed by the authors

outputs differ across the two farm size groups. In addition, the stochastic rates of growth in these variables are also different for these two groups of farms. The lowest rate of growth is observed for labour input for both groups of farms. However, the small farms showed lower rates of growth. The same pattern prevails for the other variables. Note that the values in Table 7 (and Table 8) are not adjusted for inflation.

Table 7. Average input/output values for the most influential peer farms, 2004-2016

Year	$\tilde{\phi}_{kt} > 0$, $\tilde{\theta}_{kt} < 0$					$\tilde{\phi}_{kt} > 0$, $\tilde{\theta}_{kt} > 0$				
	Labour (hours)	Herd size (LSU)	Intermediate consumption, Eur	Assets, Eur	Output, Eur	Labour (hours)	Herd size (LSU)	Intermediate consumption, Eur	Assets, Eur	Output, Eur
2004	2,835	20.9	11,727	19,831	31,386	3,411	56.0	23,639	37,032	71,685
2005	2,976	26.8	12,660	16,311	37,100	5,750	64.5	34,697	32,088	102,340
2006	4,468	24.9	14,171	45,234	37,470	6,672	118.9	79,850	66,560	194,969
2007	4,378	18.0	10,173	25,504	35,138	5,310	56.1	35,533	65,114	105,989
2008	2,859	15.0	11,895	10,226	26,847	5,963	72.3	54,010	82,226	147,812
2009	3,590	32.3	17,798	24,867	43,845	10,726	113.8	121,734	222,167	234,467
2010	3,185	15.1	11,594	32,068	30,241	5,221	66.1	63,377	88,859	141,858
2011	3,091	25.1	20,799	46,269	57,423	10,642	81.8	74,220	168,725	201,077
2013	3,724	27.0	26,411	38,863	62,681	12,520	93.1	104,507	181,289	262,466
2014	3,687	38.4	35,219	45,160	75,374	14,130	148.5	147,855	250,469	322,980
2015	3,463	32.0	20,309	36,413	52,059	14,102	196.4	258,268	428,715	488,091
2016	3,621	29.2	19,068	17,473	43,563	7,529	107.1	143,422	157,285	256,035
Rate of growth	0.7	3.9	7.7	4.4	5.7	9.6	7.4	16.8	19.2	12.8

Note: stochastic rates of growth are given.
Source: designed by the authors

Table 8. The characteristics of the most influential peer farms, 2004-2016

Year	$\tilde{\phi}_{kt} > 0$, $\tilde{\theta}_{kt} < 0$					$\tilde{\phi}_{kt} > 0$, $\tilde{\theta}_{kt} > 0$				
	Output/LSU (Eur/LSU)	Assets/labour (Eur/hour)	Intermediate consumption per LSU (Eur/LSU)	Share of hired labour	Age of farmers	Output/LSU (Eur/LSU)	Assets/labour (Eur/hour)	Intermediate consumption per LSU (Eur/LSU)	Share of hired labour	Age of farmers
2004	1,504	7	562	0.0	46	1,280	11	422	11.7	49
2005	1,384	5	472	0.0	39	1,588	6	538	0.0	56
2006	1,505	10	569	0.0	48	1,639	10	671	57.6	54
2007	1,952	6	565	0.0	34	1,889	12	633	12.7	49
2008	1,793	4	794	13.0	45	2,044	14	747	24.7	48
2009	1,358	7	551	0.0	51	2,060	21	1,070	58.5	48
2010	2,009	10	770	0.0	43	2,146	17	959	3.0	60
2011	2,287	15	828	0.0	38	2,457	16	907	56.8	48
2013	2,318	10	977	0.0	46	2,821	14	1,123	69.5	50
2014	1,965	12	918	3.5	52	2,175	18	996	67.2	53
2015	1,625	11	634	0.0	46	2,485	30	1,315	75.3	58
2016	1,492	5	653	1.5	58	2,391	21	1,339	36.4	41
Trend	32.28	0.34	25.47	0.01	0.89	105.03	1.40	77.52	4.69	-0.18

Source: designed by the authors

The relative indicators for the most influential dairy farms are presented in Table 8. As one can note, efficiency was much higher in the larger farms. In addition, the rates of change were also higher there. Initially, the difference between the large and small farms in terms of intermediate consumption per LSU was not high, yet the rate of change is much higher for the large farms and the situation changed at the end of the period covered. The asset accumulation in the large farms was much faster than in the small ones and the capital-to-labour ratio was generally higher in the large farms. Due to their large-scale operations, the large farms relied on the hired labour, as evidenced by the share of the hired labour in the total labour input. In most years, the age of the farmer was higher in the larger farms.

As we found differences in efficiency for large and small efficient farms, we also looked at the whole sample in order to ascertain which farm groups represent different regions of the RTS. This allows drawing conclusions about the losses in efficiency due to deviations from the most productive scale size. Table 9 presents the distribution of farms across different regions of the RTS and farm size/efficiency levels.

Lower requirements of intermediate consumption per output in the relatively small farms (Table 6) can be attributed to the lower milk prices if compared to the large farms. For instance, the FADN data for 2016 (LITHUANIAN INSTITUTE OF AGRARIAN ECONOMICS, 2017) indicate that the smallest farms (up to 50 ha) received an average milk price of up to 0.18 Eur/kg, whereas the large farms (more than 50 ha) received up to 0.23 Eur/kg on average. The aggregate data also show that farms below 50 ha had up to 3.1 dairy cows, whereas farms above 50 ha had up to 19.3 dairy cows on average (note that these data are provided for the whole FADN sample). These highlighted facts corroborate the existence of price discrimination according to the amount of the milk supplied.

As expected, most of the large (resp. small) farms operated under DRS (resp. IRS). The share of farms operating under IRS dropped for relatively small farms, thus indicating phasing out of unprofitable small farms. In general, both small and large farms can be scale-efficient. During 2004-2016, the pattern of farms operating in the region of CRS has been altered. Specifically, small farms dominated CRS at the end of the period (4.4% of relatively small farms and 2.4% of relatively large farms in 2016), whereas the large ones dominated at the beginning (2.5% of relatively small farms and 5.1% of relatively large farms in 2016). Thus, relatively small farms have managed to achieve the optimal scale size. However, relatively small inefficient farms still need to improve their efficiency as their share operating under DRS tended to increase (trend coefficient is 0.61 p.p.).

Finally, we decompose the variance in efficiency in order to ascertain whether farm size and efficiency combinations (relative to the average values) render

Table 9. The distribution of Lithuanian milk farms with respect to prevailing RTS and size/efficiency combinations (in per cent), 2004-2016

Year	$\tilde{\theta}_{kt} < 0$						$\tilde{\theta}_{kt} > 0$					
	$\tilde{\phi}_{kt} < 0$			$\tilde{\phi}_{kt} > 0$			$\tilde{\phi}_{kt} < 0$			$\tilde{\phi}_{kt} > 0$		
	IRS	**CRS**	**DRS**	**IRS**	**CRS**	**DRS**	**IRS**	**CRS**	**DRS**	**IRS**	**CRS**	**DRS**
2004	29.7	–	1.3	26.3	2.5	2.1	2.1	–	13.6	3.8	5.1	13.6
2005	27.9	–	3.6	27.9	2.4	1.8	4.8	–	12.7	0.6	4.8	13.3
2006	28.5	–	0.8	30.9	2.4	1.6	9.8	–	5.7	4.1	4.9	11.4
2007	25.4	–	8.1	25.4	2.3	3.5	6.9	–	8.7	8.1	5.2	6.4
2008	31.4	–	1.0	25.8	3.6	1.0	5.7	–	8.2	3.6	6.2	13.4
2009	22.2	–	17.5	20.6	2.6	4.2	4.2	–	9.0	3.7	4.2	11.6
2010	29.4	–	4.3	29.0	1.7	2.3	5.9	–	7.3	4.6	3.6	11.9
2011	21.9	–	21.9	15.2	3.2	6.1	1.0	–	9.0	3.2	2.6	15.8
2012	34.7	–	2.9	25.6	2.9	0.6	7.1	–	6.5	5.8	3.2	10.4
2013	29.4	–	5.8	25.2	2.9	4.8	6.1	–	6.8	4.2	3.5	11.3
2014	28.4	–	9.1	23.9	4.6	2.5	5.3	–	6.3	6.7	4.2	9.1
2015	27.9	–	9.8	24.9	4.0	2.4	2.4	–	8.8	4.4	2.4	13.1
2016	33.8	–	8.8	18.2	4.4	3.0	2.4	–	9.1	3.4	2.4	14.5
Trend	0.24	–	0.61	-0.54	0.16	0.09	-0.17	–	-0.29	0.10	-0.24	0.05

Note: the figures given are relative to the sample size for a particular year; IRS, CRS, and DRS denote farms operating at increasing, constant, and decreasing returns to scale, respectively.
Source: designed by the authors

Table 10. Decomposition of the efficiency variance into within-group and between-group components

Year	$\tilde{\theta}_{kt} < 0$				$\tilde{\theta}_{kt} > 0$				Total var
	$\tilde{\phi}_{kt} < 0$		$\tilde{\phi}_{kt} > 0$		$\tilde{\phi}_{kt} < 0$		$\tilde{\phi}_{kt} > 0$		
	Var	Contribution (per cent)	Var	Contribution (per cent)	Var	Contribution (per cent)	Var	Contribution (per cent)	
Within-group									
2004	0.0030	42.2	0.0015	21.6	0.0016	22.1	0.0010	14.1	0.0072
2005	0.0018	33.2	0.0017	30.4	0.0015	27.1	0.0005	9.3	0.0056
2006	0.0024	37.9	0.0012	19.8	0.0022	34.3	0.0005	8.0	0.0063
2007	0.0027	42.2	0.0014	22.2	0.0015	23.0	0.0008	12.6	0.0065
2008	0.0027	42.5	0.0015	23.3	0.0008	12.8	0.0014	21.4	0.0063
2009	0.0033	45.2	0.0019	26.2	0.0007	9.6	0.0014	19.0	0.0073
2010	0.0033	49.4	0.0014	21.3	0.0011	16.6	0.0008	12.8	0.0066
2011	0.0033	46.5	0.0019	26.7	0.0004	5.6	0.0015	21.1	0.0070
2012	0.0028	47.0	0.0016	27.8	0.0006	10.1	0.0009	15.0	0.0059
2013	0.0033	50.0	0.0016	24.3	0.0008	11.4	0.0010	14.3	0.0067
2014	0.0030	43.0	0.0019	27.0	0.0009	13.4	0.0012	16.6	0.0070
2015	0.0034	41.9	0.0028	33.7	0.0007	8.2	0.0013	16.2	0.0082
2016	0.0046	57.3	0.0015	18.7	0.0007	8.3	0.0013	15.7	0.0080
Between-group									
2004	0.0058	30.8	0.0049	26.5	0.0042	22.7	0.0037	19.9	0.0187
2005	0.0050	28.5	0.0041	23.7	0.0038	22.0	0.0045	25.9	0.0174
2006	0.0057	35.1	0.0045	28.0	0.0032	20.2	0.0027	16.7	0.0161
2007	0.0078	38.4	0.0063	31.1	0.0026	12.6	0.0037	17.9	0.0204
2008	0.0074	39.4	0.0051	27.2	0.0027	14.2	0.0036	19.1	0.0188
2009	0.0094	44.1	0.0065	30.8	0.0009	4.2	0.0044	20.8	0.0212
2010	0.0067	39.2	0.0049	28.6	0.0024	13.9	0.0031	18.3	0.0172
2011	0.0072	41.7	0.0056	32.1	0.0008	4.7	0.0037	21.5	0.0174
2012	0.0060	38.6	0.0049	31.1	0.0016	10.2	0.0032	20.1	0.0156
2013	0.0085	48.3	0.0050	28.3	0.0009	5.0	0.0032	18.4	0.0176
2014	0.0075	42.2	0.0055	30.9	0.0016	8.8	0.0032	18.1	0.0179
2015	0.0093	47.0	0.0064	32.2	0.0010	4.9	0.0032	15.9	0.0199
2016	0.0101	42.1	0.0085	35.5	0.0010	4.3	0.0043	18.1	0.0239

Source: designed by the authors

different levels of efficiency and whether farms are homogenous within those groups. This allows quantifying the dynamics in heterogeneities revealed by Figure 2. The decomposition of the variance of the efficiency with respect to the four (out of nine possible as shown in Eq. 7) groups of farms following KARAGIANNIS and PALEOLOGOU (2018) is carried out as:

$$\operatorname{var}(\phi_{kt}) = \sum_{h=1}^{9} p_{ht} \operatorname{var}(\phi_{ht}) + \sum_{h=1}^{9} p_{ht} \left(\bar{\phi}_{ht} - \bar{\phi}_{t}\right)^2, \quad (10)$$

where h is the index of farm groups based on the farm size/efficiency combinations, p_{ht} is the proportion of observations in group h during period t and variables with bars denote respective averages. Therefore, the first term on the right-hand side of Eq. 10 captures the within-group variance, whereas the second term accounts for the between-group variance. Table 10 presents the results of the variance decomposition.

Between-group variance dominated over the within-group variance during 2004-2016. This indicates that the farms are more heterogeneous (in terms of TE) across different groups rather than within the groups defined by farm size and efficiency level. The highest variance is observed in the relatively small farm group (independently of the level of efficiency). The same finding applies to both within- and between-group terms. Therefore, small farms are more diverse in their efficiency levels and these groups are further from the sample average. The share of contributions to the overall variance from the small farms increased over time. Therefore, it is necessary to ensure spill-over of state-of-the-art farming practices and improve managerial abilities for the small farms in order to improve their TE and decrease heterogeneity in that sub-sector. Development of effective extension services may be beneficial in this instance.

5 Discussion

This study reported average annual efficiency scores of 0.75-0.84 for the period 2004-2016. This is comparable to the results reported by, for example, SKEVAS (2020), who calculated a mean efficiency of 0.843 for Dutch dairy farms, or SKEVAS et al. (2018b), who obtained an estimate of 0.7 for German dairy farms. This indicates that Lithuanian dairy farms are rather heterogeneous in their performance (compared to, for example, those of the Czech Republic, as discussed by ZAKOVA KROUPOVA (2016).

DERVILLÉ et al. (2017) noted that the dynamics in dairy farm structure is impacted by a plethora of factors, both internal and external (contextual) ones. Economies of scale and scope were identified as positively contributing to the probability of taking decisions to stay in farming in the case of French farmers. From the viewpoint of TE in our study, we note that both relatively small and large farms can be efficient. Thus, diversification (economies of scope) can be a valid option for compensating for loss in productivity due to deviation from the most optimal scale size DONG et al. (2017) investigated the TE of US dairy farms and suggested that both the probability to stay in farming and herd size increases with TE. Thus, one may expect relatively small efficient farms to embark on expansion in the future.

KUIPERS et al. (2017) compared the business strategies of dairy farmers in Lithuania, Netherlands, Slovenia and Poland. The results indicated that, compared to the other countries, Lithuanian dairy farmers were more prone to expand their farms and acknowledge their lack of expertise in modern farming practices. Another group of Lithuanian farmers indicated they were likely to postpone decisions on farm expansion. These results also confirm that Lithuanian farmers are diverse in their farming intentions and their achieved level of performance (which can be measured via TE).

6 Conclusions

Dominated by relatively small farms, the Lithuanian dairy sector faces difficulties in operation of its milk supply chain. Due to a fragmented milk supply, the small producers often receive lower prices, even when Lithuania already has one of the lowest raw milk prices in the EU. Such a situation implies the need for structural changes. In this paper, we attempted to analyse the dynamics in aggregate efficiency with respect to farm size to evaluate the impacts of ongoing structural changes upon TE.

The decomposition of the aggregate efficiency confirmed the impact of the restructuring on sector-level efficiency. Specifically, the covariance term tended to increase during 2004-2016, thus indicating the increasing importance of the linkages between farm size and TE. The decomposition also showed that the relatively small low-efficiency farms contributed to the covariance term, thus confirming the phasing out of inefficient farms.

The identification of the most influential peer dairy farms allowed us to describe two models to follow in Lithuanian dairy farms, i.e. small- and large-scale farms. An average herd size for the relatively large farms of up to 200 LSU was observed, whereas the corresponding limit for the relatively small farms was some 40 LSU. The increased herd size was related to a higher share of hired labour. Adopting a reasonable farm structure may ensure successful operation of Lithuanian dairy farms which have access to resource endowments needed for this type of farming (grasslands and water resources).

Variance decomposition indicated that it was the relatively small farms that rendered the highest contribution to the between- and within-group variance (the groups were defined in terms of farm size/ efficiency combinations). This implies these farms are both heterogeneous among themselves and deviate from the sample average in the sense of TE. Accordingly, public support is needed to guide the restructuring of dairy farms in Lithuania, with particular focus on underperforming relatively small farms.

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