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Estimation of technical efficiency of Czech farms operating in less favoured areas

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Abstract: This paper deals with the technical efficiency analysis of farms in the Czech Republic. The empirical analysis provides an evaluation of technical efficiency with regard to the farm size, farm specialisation, and farm location. Accounting data of Czech farms from the Albertina database for the years 2011–2015 were used for the analysis. The data were classified by the utilised agricultural area and location of the farm expressed as a less favoured area type from the Land Parcel Identification System (LPIS) database. Research was conducted using the translogarithmic production function and Stochastic Frontier Analysis. The results indicate positive impact of farm size, expressed by utilised agricultural area, on technical efficiency. The analysis of the impact of farm specialisation on technical efficiency verified that farms specialised on animal production are more efficient. The lowest technical efficiency is shown by farms situated in mountainous Less Favoured Areas (LFAs), the highest technical efficiency by farms located in non-LFA regions.

Keywords: agriculture; Less Favoured Areas (LFA); specialisation; Stochastic Frontier Analysis; technical efficiency

Over the past two decades, there have appeared several papers and studies related to the analysis of efficiency and productivity in agricultural economics, applying different approaches, methods, and data sources. Efficiency and productivity have been considered an indicator of competitiveness, and questions linked to the efficiency and productivity analysis of different groups of farms have also been of significant interest for policy makers. Using a given quantity of input, technically inefficient farms cannot produce as much output as more efficient farms or they use more inputs to produce a given output. Therefore, their average costs are higher compared to more efficient farms (Kumbhakar and Lovell 2000). The differences in technical efficiency (TE) can be explained by the environment in which the farm operates (e.g. land quality, higher altitude). Latruffe et al. (2017) analysed dairy farms in selected European countries, the results showing negative effect of an unfavourable environment, represented by Less Favoured Areas (LFAs), on output. A similar effect is shown in the paper by Oxouzi et al. (2012) or in Palkovic et al. (2014). Barath et al. (2018) analysed differences in technical efficiency between Slovenian farms in LFAs and those in non-LFAs. They found out that the farms in LFAs showed lower efficiency but the difference in comparison to non-LFAs was small and not statistically significant. The authors argue that the farms in LFAs may have larger variation in output due to their limited natural agricultural factor endowments. Other reasons are related to the quality of management, labour and material inputs.

The studies related to Czech agricultural productivity and efficiency analysis were conducted by several authors. Jurica et al. (2004) analysed the structural changes and efficiency of Czech agriculture in the pre-EU-accession period. Jelinek (2006) studied the relationship between technical efficiency and technological change in milk production in the Czech Republic. Using Data Envelopment Analysis, Davi-

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dova and Latruffe (2007) investigated the relationship between farm financial structure and technical efficiency in Central and Eastern European farming during the transition to a market economy. The authors concluded that former collective and state farms are more efficient than individual farms. Cechura (2010, 2012) identified the key factors determining the efficiency of input use and the development of total factor productivity (TFP) in Czech agriculture and the food processing industry. The author concluded that the developments in the individual branches are characterised by idiosyncratic factors, as well as the systemic effect, especially in animal production. The most important factors determining both the technical efficiency and TFP are those connected with institutional and economic changes. Mala (2011) investigated the technical efficiency of Czech organic farms and compared it to the efficiency of conventional farms using a Stochastic Frontier Approach.

Analyses of technical efficiency and performance of farms located in less favoured areas (LFAs) in the Czech Republic have been provided by only a few authors. Cechura (2014) provided an analysis of the relationship between farm size and technical and scale efficiency. Using the SFA (Stochastic Frontier Analysis) approach the author concluded that significant differences between efficiency and farm size exist only for the technical efficiency of farms with more than 1 000 ha. Matulova and Cechura (2016) investigated differences in the TE of farms located in LFA and non-LFA and concluded that there is no statistically significant relationship between technical efficiency and the farm location. The authors explained this fact by pointing to subsidies, which were applied more efficiently by agricultural companies located in the LFA.

Stolbova and Micova (2012) provided a structural survey of agriculture in the Czech Republic (CR). The results of the analysis proved that both human labour and machinery are used more effectively by the large farms, situated in an LFA, than by the small farms. Even more successful are the extensive farms in mountain areas that are, however, highly dependent on support aid (Lososova and Zdenek 2013). The most threatened farms, in the authors' opinion, are those situated in LFAs (other) and focusing on mixed plant and livestock production. Lososova and Zdenek (2014) provide an analysis of farm profitability in the Czech Republic. They investigated the impact of factors such as profits and profitability, efficiency of production factors, debt, financial health, and dependence on subsidies. The authors confirm that the highest dependence on subsidies can be identified in farms located in mountain LFAs. Farms focusing on plant production are less dependent on subsidies, but these farms are more sensitive to climate change and price development.

However, a detailed analysis of farms in LFA is missing. Moreover, in most cases, the analysed period is not relevant to the requirements of policy makers.

The aim of this article is to evaluate the differences in technical efficiency between different farm sizes, their location, and specialisation using a Stochastic Frontier Analysis (SFA), True Random Effects model (REM) (Greene 2005). The research questions to be addressed are:

i) What is the average level of technical efficiency of Czech farms?

ii) Are there significant differences in technical efficiency between different groups of farms according to their specialisation, size and LFA type?

MATERIAL AND METHODS

Data input

The panel data set was collected from the Albertina database (Bisnode 2017), complemented by the land areas of farms from LPIS database (Ministry of Agriculture of the Czech Republic 2017a), and the number of livestock units (LU) from the Register of Animals (Ministry of Agriculture of the Czech Republic 2017b). The analysis uses information from financial statements of companies whose main activity is agriculture (plant and/or animal production) in the period from 2011 to 2015. After the cleaning process (checking that the branch of an enterprise is correct, removing companies with missing observations and negative values for the variables), the unbalanced panel data set contained 10 088 observations.

The following variables were used in the analysis: Output, Land, Labour, Capital, Material input (material and energy). Output is represented by the total sales of goods, products, and services of the agricultural company. To avoid price changes, Output was deflated by the price index of agricultural companies. Land variable is expressed by utilised agricultural area by farm, extracted from LPIS database. The Labour input is used in the form of total personnel costs per company. The Capital variable is represented by the value of tangible assets. Material input is the total costs of material and energy consumption per company. Capital and Material were deflated by the price index of the industrial sector. Table 1 represents descriptive characteristics of the dataset.

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Table 1. Descriptive characteristics of data set (thousand EUR/farm)

Variable	Mean (thousand EUR)	Standard deviation (thousand EUR)	Coefficient of variation
Output (y)	2 454.23	23 862.03	957.34
Land (ha),(x_1)	44.34	42.32	95.44
Capital (x_2)	4 759.94	65 657.11	1 379.37
Labour (x_3)	550.25	5 278.60	959.31
Material (x_4)	1 325.68	6 704.66	505.75

the data in the database are originally in CZK; numbers were recalculated to EUR using the exchange rate of Czech National Bank

Source: own processing

The farm specialisation was defined according to government regulation No. 43/2018 Sb. Two types of farms were considered. Farms with predominant plant production (PP) include farms with a burden of ruminants less than 0.3 LU per ha of agricultural land. Farms with predominant animal production (AP) include farms with a burden of ruminant equal or higher than 0.3 LU per ha of agricultural land.

The inclusion of enterprises by the LFA type was done according to the following key: LFA-M farms are those that have more than 50% of their utilised agricultural area (UAA) in the LFA mountain area. The LFA-S farm category includes farms with more than 50% of UAA in an area with specific constraints. The LFA-O farm category represents farms with more than 50% of their UAA in other LFAs, and the LFA-N farms have more than 50% of their UAA in non-LFA areas.

The farm size division applied for the paper reflects the categorisation used for determining the degressivity of the LFA payments:
– area of up to 300 ha,
– area of over 300 ha up to (and including) 500 ha,
– area of over 500 ha up to (and including) 900 ha,
– area of over 900 ha up to (and including) 1 800 ha,
– area of over 1800 ha up to (and including) 2 500 ha,
– area of over 2 500 ha.

Stochastic Frontier Analysis (SFA)

To study the determinants of technical efficiency we used the SFA methodology developed by Aigner et al. (1977). Stochastic frontier models allow for an analysis of technical inefficiency in the framework of production functions. The SFA method is based on an econometric (i.e. parametric) specification of a production frontier. Using a generalised production function and cross-sectional data, this method can be depicted as follows:

$$y_i = f\left(x_{ij};\beta\right) \times \exp\left(\varepsilon_i\right) \quad (1)$$

where y represents output, x is a vector of inputs, β is a vector of unknown parameters, and ε is the error term. The subscripts i and j denote the firm and inputs, respectively.

In this specific formulation, the error term is farm-specific and is composed of two independent components: $\varepsilon_i = v_i - u_i$. The first element, v_i, is a random variable reflecting noise and other stochastic shocks entering the definition of the frontier, such as weather, luck and strikes. This term is assumed to be an independent and identically distributed normal random variable with zero mean and constant variance iid $\left[\mathrm{N} \sim \left(0,\sigma_v^2\right)\right]$.

The second component u_i, captures technical inefficiency relative to the stochastic frontier. The inefficiency term u_i is nonnegative and it is assumed to follow a half-normal distribution (Kumbhakar and Lovell 2000).

An index for TE (technical efficiency) can be defined as the ratio of the observed output (y) and maximum feasible output (y^*):

$$TE_i = \frac{y_i}{y_i^*} = \frac{f\left(x_{ij};\beta\right) \times \exp\left(v_i - u_i\right)}{f\left(x_{ij};\beta\right) \times \exp\left(v_i\right)} = \exp\left(-u_i\right) \quad (2)$$

Because $y \leq y^*$, the TE index is bounded between 0 and 1; TE achieves its upper bound when a firm is producing the maximum output feasible level (i.e. $y = y^*$), given the input quantities. Jondrow et al. (1982) demonstrated that farm-level TE for half-normal distribution of inefficiency term can be calculated from the error term ε_i as the expected value of $-u_i$ conditional on ε_i, which is given by:

$$E\left[u_i \mid \varepsilon_i\right] = \frac{\sigma_u \sigma_v}{\sigma}\left[\frac{\phi\left(\varepsilon_i \lambda / \sigma\right)}{1 - \Phi\left(\varepsilon_i \lambda / \sigma\right)} - \frac{\varepsilon_i \lambda}{\sigma}\right] \quad (3a)$$

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where $\sigma^2 = \sigma_u^2 + \sigma_v^2$, $\lambda = \sigma_u / \sigma_v$, $\phi(\cdot)$ represent the standard normal density and $\Phi(\cdot)$ the standard normal cumulative density functions.

In the case of exponential distribution of inefficiency, the farm-level TE is calculated in the form:

$$E[u_i \mid \varepsilon_i] = \tilde{\mu}_i + \sigma_v \left[\frac{\phi(-\tilde{\mu}_i / \sigma_v)}{1 - \Phi(\tilde{\mu}_i / \sigma_v)} \right] \tag{3b}$$

where $\tilde{\mu} = -\varepsilon - \sigma_v^2 / \sigma_u$.

Thus, the TE measure for each farm is equal to:

$$TE_i = \exp\left(-E[u_i \mid \varepsilon_i]\right) \tag{4}$$

"True" random effects model (TRE)

In the fixed-effects model it is assumed that the inefficiency term is fixed and that correlation with regressors is allowed. Unlike the fixed effects model, the opposite situation is considered, in which the u_i are randomly distributed with constant mean and variance but are assumed to be uncorrelated with the regressors and the v_{it}. The random effects specification assumes that the firm-specific inefficiency is the same every year, i.e. the inefficiency term is time invariant. In these propositions, the model absorbs all unmeasured heterogeneity in u_i.

Greene (2005) argued that the random effects model with the proposed extensions has three significant weaknesses. The first is its implicit assumption that the effects are not correlated with the included variables. The second problem with the random effects is its hypothesis that the inefficiency is the same in every period. For long time series data, this is likely to be an undesirable assumption. The third shortcoming of this model is that in this model, u_i carries both the inefficiency and, in addition, any time-invariant firm-specific heterogeneity. To avoid the former limitations Greene (2005) proposed "True" random effects model that is as follows:

$$y_{it} = \alpha + \beta' x_{it} + w_i + v_{it} - u_{it} \tag{5}$$

where α is a constant, β´ is a vector of unknown parameters, w_i is the random, firm-specific effect and v_{it} and u_{it} are the symmetric and one sided components specified earlier.

Since the heterogeneity of farms had been proven by many studies (Cechura 2010; Matulova and Cechura 2016), True Random Effects model was chosen as an appropriate tool.

The Spearman and Kendall correlation coefficients were used to assess the relationship between factors that are supposed to have impact on farm performance and technical efficiency.

RESULTS AND DISCUSSION

Estimation of technical efficiency of Czech farms

The empirical analysis is based on an estimation of the translogarithmic production function in which both the output and inputs are expressed in logarithmic form and normalised by their arithmetic means. The inefficiency term is assumed to have exponential distribution.

The translogarithmic production function was estimated in the following form:

$$\ln y_{it} = \beta_0 + \sum_{j=1}^{J} \beta_j \ln x_{jit} + \beta_t t + \frac{1}{2} \sum_{j=1}^{J} \sum_{k=1}^{K} \beta_{jk} \ln x_{jit} \ln x_{kit} + \\ + \frac{1}{2} \beta_{tt} t^2 + \sum_{j=1}^{J} \beta_{jt} \ln x_{jit} t + \varepsilon_{it} \tag{6}$$

where β is a vector of unknown parameters, y is an output variable, x are input variables, t is the time vatiable, ε is the error term; the subscript i denotes a firm, subscripts j and k denote inputs.

The first-order estimated parameters Land (x_1), Capital (x_2), Labour (x_3), and Material input (x_4) are significant under z-test at 1% level of significance (Table 2). The parameter Land (x_1) variable is significant at 5% level of significance. This means that these variables (x_1, x_2, x_3, x_4, x_5) have a significant impact on total production. Signs of the coefficients are positive, which is consistent with economic theory (the assumption of monotonicity is fulfilled). The curvature condition of quasi-concavity in inputs (diminishing marginal productivity for each input) is achieved in the case of all production factors. Since the values of production factors were normalised by their arithmetic means after logarithmic transformation, in translogarithmic model these coefficients represent elasticities, that is, possible percentage change in aggregate output because of one percent change in input. All production elasticities are negative; the highest elasticity is displayed by Material input (0.58480). If the Material input changes by one percent, the production will change by 0.52480%. The lowest elasticity belongs to the production factor Land (0.01419). If the Land input

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Table 2. Estimation results of TRE model

y	Coefficient	Std. error	z	$P > z$
First-order parameters				
x_1	0.01419	0.00696	2.04	0.042
x_2	0.10533	0.00640	16.46	0.000
x_3	0.19866	0.00995	19.97	0.000
x_4	0.58480	0.00974	60.02	0.000
t	–0.02915	0.00118	–24.70	0.000
Constant	0.24290	0.01039	23.39	0.000
Second-order parameters				
x_{11}	–0.00367	0.00261	–1.40	0.160
x_{22}	0.00832	0.00049	16.96	0.000
x_{33}	0.05524	0.00451	12.25	0.000
x_{44}	0.04252	0.00113	37.68	0.000
tt	0.05530	0.00134	41.12	0.000
x_1x_2	–0.00437	0.00066	–6.61	0.000
x_1x_3	–0.02942	0.00289	–10.18	0.000
x_1x_4	0.00773	0.00206	3.75	0.000
x_2x_3	–0.00817	0.00094	–8.67	0.000
x_2x_4	0.00634	0.00070	9.00	0.000
x_3x_4	–0.03164	0.00309	–10.24	0.000
x_1t	0.00199	0.00071	2.80	0.005
x_2t	0.00046	0.00076	0.60	0.548
x_3t	0.00326	0.00185	1.76	0.078
x_4t	–0.00570	0.00168	–3.40	0.001
Other parameters				
Usigma				
Constant	–2.36700	0.02370	–99.86	0.000
Vsigma				
Constant	–6.65330	0.14071	–47.28	0.000
Theta				
Constant	0.73777	0.00585	126.10	0.000
Sigma_u	0.30621	0.00363	84.38	0.000
Sigma_v	0.03591	0.00253	14.21	0.000
Lambda	8.52629	0.00488	1 746.55	0.000

TRE – true random effects model; y – output; x_1 – land; x_2 – capital; x_3 – labour; x_4 – material; t – time variable; z – value – test statistic for z-tests that measures the difference between an observed statistic and its hypothesised population parameter in units of the standard deviation; $P > z$ – probability that you have falsely rejected the null hypothesis (null hypothesis: estimated parameter is close to 0, or insignificant)

Source: own processing based on Albertina and LPIS database (Bisnode 2017; Ministry of Agriculture of the Czech Republic 2017a)

changes by one percent, the production will change by 0.01419%. Technical change has a negative impact on production (the variable Time (t) is positive and significant at 1% level of significance). Moreover, the impact of technical change accelerated over time (tt > 0). It is characterised by Land-, Labour- and Capital-intensive, and Material-saving behaviour. The sector is characterised by slightly diminishing returns to scale. Technical efficiency of the whole sector is equal to 71.5 %.

Impact of farm size and specialisation on technical efficiency

The next step of the analysis was based on a division of the whole dataset into groups according to size of the farms expressed by the utilised agricultural area using the previous estimation. The results are represented in Table 3.

The highest number of observations belongs to farms with 900–1 799 ha and less than 300 ha of UAA. Table 3 shows that farms with larger land area have higher technical efficiency. In addition, the standard deviation is decreasing, indicating that the set of larger farms is more homogeneous, i.e. the technical efficiency of larger farms approaches average technical efficiency within the given farm group.

In addition, a correlation between the size of the farm and technical efficiency was analysed. The Spearman and Kendall correlation coefficients indicate a significant positive relationship between technical efficiency and farm size, expressed by the UAA.

The technical efficiency of farms with animal production is higher than the technical efficiency of farms with plant production (Table 4).

Impact of farm location (type of LFA) on technical efficiency

The analysis in this part was provided by two methods: first, correlation analysis was applied to the first estimation of the production function of the whole dataset. Then, the dataset was divided into four datasets according to farm location (type of LFA), and production function for each dataset was estimated.

The correlation between the technical efficiency, estimated for the whole dataset, and the farm location, was tested using Spearman and Kendall correlation coefficients. The dummy variables 1 to 4 were generated for the individual areas. The highest technical efficiency is shown by the farms located in non-LFAs;

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Table 3. Technical efficiency of farms according to farm size

Farm size (ha UAA)	Number of observations	Mean	Standard error	Minimum value	Maximum value
< 300	2 143	0.59505	0.28646	0.000	0.95660
300–499	932	0.69773	0.22365	0.000	0.95482
500–899	1 926	0.71513	0.20367	0.000	0.95958
900–1 799	2 923	0.75904	0.16076	0.000	0.97438
1 800–2 499	1 175	0.76805	0.15096	0.000	0.94153
≥ 2 500	977	0.77266	0.13168	0.075	0.94518

UAA – utilised agricultural area

Source: own processing based on Albertina and LPIS database (Bisnode 2017; Ministry of Agriculture of the Czech Republic 2017a)

Table 4. Technical efficiency of farms according to specialisation

Specialisation	Number of observations	Mean	Standard error	Minimum value	Maximum value
Plant production	5 590	0.67958	0.23064	0.000	0.95958
Animal production	4 498	0.75322	0.18552	0.000	0.97438

Source: own processing based on Albertina and LPIS database (Bisnode 2017; Ministry of Agriculture of the Czech Republic 2017a)

the dummy variable 1 was assigned to these farms. Other LFA types with assigned dummy variables were as follows: LFA-O – "2", LFA-S –"3", LFA-M – "4".

Spearman and Kendall correlation coefficients indicate a significant (10% level of significance) negative correlation between technical efficiency and farm location in individual areas. According to the results of the correlation analysis, the lowest technical efficiency belongs to LFA-M farms.

In the next step, the whole dataset was divided into four groups of farms according to their location in a mountain area (LFA-M), area with specific

Table 5. Estimated parameters of production function for the group of farms with different location

y	LFA-M*		LFA-S		LFA-O		LFA-N	
	coefficient	$P > z$	coefficient	$P > z$	coefficient	$P > z$	coefficient	$P > z$
x_1	0.01940	0.000	0.04286	0.000	–0.05191	0.000	0.03352	0.001
x_2	0.04638	0.000	0.04409	0.000	0.08301	0.000	0.12637	0.000
x_3	0.32312	0.000	0.28766	0.000	0.24495	0.000	0.19907	0.000
x_4	0.66912	0.000	0.66871	0.000	0.57590	0.000	0.56677	0.000
t	–0.02345	0.000	–0.01047	0.000	–0.03217	0.000	–0.02991	0.000
Constant	–0.19765	0.000	–0.14665	0.000	0.23920	0.000	0.35343	0.000
x_1t	0.00040	0.000	–0.00032	0.000	0.00059	0.639	0.00353	0.000
x_2t	0.00106	0.000	–0.00494	0.000	–0.00304	0.003	–0.00244	0.011
x_3t	–0.01633	0.000	0.01415	0.000	0.01027	0.003	0.00347	0.103
x_4t	0.00261	0.000	0.00487	0.000	–0.00819	0.008	–0.00192	0.377
Lambda	12.81	0.000	5.93	0.000	10.65	0.000	0.35	0.000
RTS	1.058		1.043		0.852		0.926	

*four groups of farms according to their location in a mountain area (LFA-M), area with specific constraints (LFA-S), other areas (LFA-O), or non-LFA areas (LFA-N); y – output; x_1 – land; x_2 – capital; x_3 – labour; x_4 – material; t – time variable; RTS – return to scale

Source: own processing based on Albertina and LPIS database (Bisnode 2017; Ministry of Agriculture of the Czech Republic 2017a)

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Table 6. Technical efficiency of farms according to their location

Area*	Number of observations	Mean of TE	Standard error	Minimum value of TE	Maximum value of TE
LFA-M	1 369	0.56829	0.27253	0.000	0.95332
LFA-S	580	0.60342	0.26997	0.000	0.99944
LFA-O	2 932	0.71827	0.20884	0.000	0.98588
LFA-N	5 113	0.75879	0.19232	0.000	0.96809

*four groups of farms according to their location in a mountain area (LFA-M), area with specific constraints (LFA-S), other areas (LFA-O), or non-LFA areas (LFA-N); TE – technical efficiency

Source: own processing based on Albertina and LPIS database (Bisnode 2017; Ministry of Agriculture of the Czech Republic 2017a)

constraints (LFA-S), other areas (LFA-O), or non-LFA areas (LFA-N).

The estimated parameters of the production function are shown in Table 5.

Estimates of the first-order parameters (x_1, x_2, x_3, x_4) are significant at 1% level of significance. Parameter estimates (except the estimates for LFA-O) are consistent with economic theory, i.e. they fulfil the assumption of monotonicity – they are not decreasing in inputs. LFA-M and LFA-S farms have increasing returns to scale, while LFA-O and non-LFA farms are characterised by decreasing returns to scale. Therefore, these farms could achieve better results by increasing the size of production using given technology.

The technical efficiency of farms according to LFA is shown in Table 6. The least technically efficient farms are situated in mountain areas (LFA-M; TE = 56.83%), followed by areas with specific constrains (LFA-S; TE = 60.34%), and, finally, in other LFAs (LFA-O; TE = 71.83%). Farms that are not situated in LFAs (LFA-N) have the highest technical efficiency (75.88%). Moreover, LFA-M farms are the most heterogeneous – the standard deviation of technical efficiency is the highest for this group of farms. As technical efficiency increases, the standard deviation, conversely, decreases.

The development of technical efficiency over time has a fluctuating trend (Figure 1). LFA-M and LFA-S farms have the largest variations. The technical efficiency of LFA-O and non-LFA farms is more stable over time. The linear trend indicates a slightly increasing technical efficiency over time for farms in all areas, except the LFA-S farms where the trend over time is stagnant.

The results in Table 7 confirm the previous results. The level of technical efficiency of livestock farms is higher than the technical efficiency of farms with crop production. Non-LFA farms show the highest efficiency, LFA-M farms the lowest.

The results of this paper are in line with the results of previous studies. Cechura (2014) proved the existence of a difference in technical efficiency

Table 7. Technical efficiency according to location and specialization

Area and specialization*	Number of observation	Mean of TE	Standard error	Minimum value of TE	Maximum value of TE
LFA-M PP	327	0.49844	0.24570	0.000	0.87467
LFA-M AP	1 042	0.63099	0.27349	0.000	0.97045
LFA-S PP	274	0.59466	0.26240	0.000	0.99499
LFA-S AP	306	0.85477	0.11088	0.156	0.97463
LFA-O PP	1 122	0.61580	0.24258	0.000	0.97942
LFA-O AP	1 810	0.82984	0.17033	0.000	0.97091
LFA-N PP	3 822	0.72638	0.20471	0.000	0.95502
LFA-N AP	1 291	0.89651	0.10263	0.000	0.98306

*four groups of farms according to their location in a mountain area (LFA-M), area with specific constraints (LFA-S), other areas (LFA-O), or non-LFA areas (LFA-N); PP – plant production; AP – animal production; TE – technical efficiency

Source: own processing based on Albertina and LPIS database (Bisnode 2017; Ministry of Agriculture of the Czech Republic 2017a)

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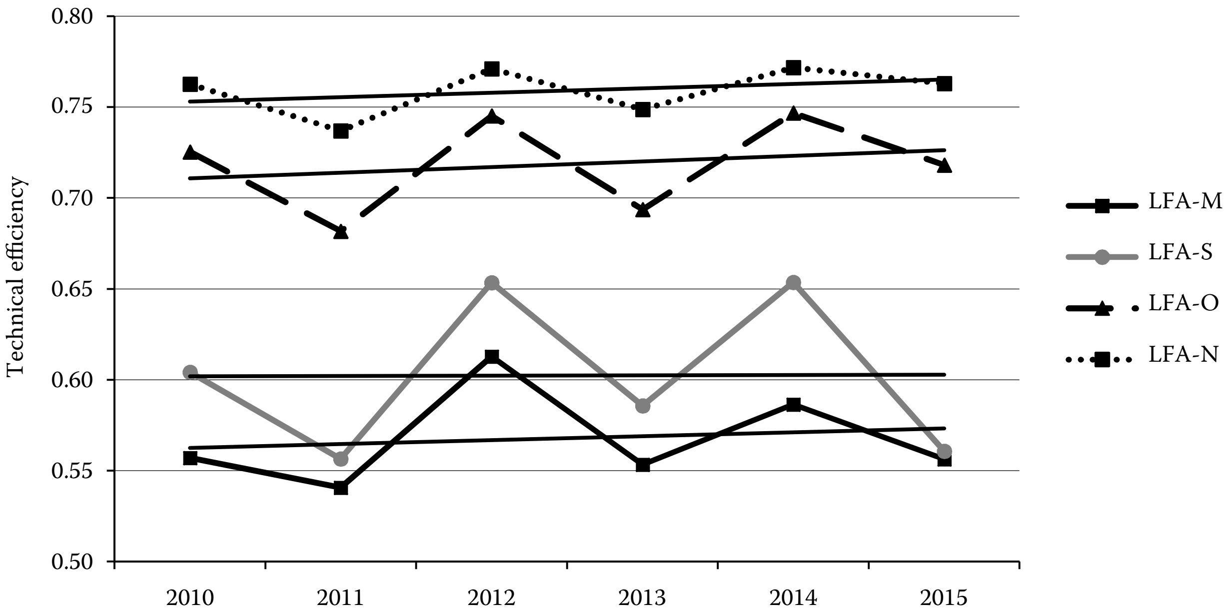

Figure 1. Development of technical efficiency in time

four groups of farms according to their location in a mountain area (LFA-M), area with specific constraints (LFA-S), other areas (LFA-O), or non-LFA areas (LFA-N)

Source: own processing based on Albertina and LPIS database (Bisnode 2017; Ministry of Agriculture of the Czech Republic 2017a)

of the different sized farms. However, the author showed that farms with more than 1 000 ha have significantly higher technical efficiency. The results of our paper demonstrate a significant difference in efficiency between farms operating with less than 300 ha and those operating with more than 300 ha. The next significant difference was proven between farms with less than 900 ha and those with more than 900 ha of land area. Stolbova and Micova (2012) verified a more effective use of both the human labour and machinery by the large farms, situated in the LFA, than by the small farms.

The results evidenced the difference in technical efficiency of farms according to location (Oxouzi et al. 2012; Palkovic et al. 2014; Latruffe et al. 2017). The farms that operate in LFA mountain areas have the lowest technical efficiency. However, Matulova and Cechura (2016) did not prove the statistically significant relationship between technical efficiency and farm location. The authors explained this fact by the subsidies that were applied more efficiently by agricultural companies located in LFAs.

This paper has proven that farms with plant production have lower technical efficiency than farms with animal production. Moreover, the most threatened farms are the LFA-M (mountain) farms, while the most successful farms are those operating in non-LFA areas. According to Lososova and Zdenek (2014), even more successful are the extensive farms in mountain areas that are, however, highly dependent on support aid. The most threatened farms, in the authors' opinion, are farms situated in other LFAs that focus on mixed plant and livestock production. Moreover, Lososova and Zdenek (2014) confirm that the LFA-M (mountain) farms are highly dependent on subsidies.

CONCLUSION

The aim of this paper was to find out whether the technical efficiency differs according to the size of the farm and its specialisation and how the farm's location in the individual types of LFAs or in non-LFA areas influence its technical efficiency. Farms operating in LFAs were expected to produce less efficiently due to natural constraints.

Technical efficiency was estimated using the Stochastic Frontier Analysis (SFA) approach. The translogarithmic production function was estimated using the True Random Effects model which considers unobservable heterogeneity.

Average technical efficiency was estimated over the whole dataset and then calculated for different

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farm groups according to different farm sizes, specialisations, and locations. Larger farms (according to the utilised agricultural area) achieve higher technical efficiency. In this case, subsidies for small farms could be a tool for compensating for the disadvantages resulting from the farm size. Farms specialising in animal production achieve a higher level of technical efficiency than farms with plant production.

The results showed that farms located in areas outside LFAs (non-LFA) have better farming conditions, resulting in achieving better results. The least technically efficient are farms that operate in mountain areas (LFA-M), then in areas with specific constraints (LFA-S) and finally in other areas (LFA-O). The highest technical efficiency is reached by the farms in non-LFA regions. These findings are an important message for policy makers with respect to the setting of CAP subsidies for the next programming period.

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