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Technical efficiency and its determinants for Czech livestock farms

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Abstract: Organic farming has become an important part of Czech agriculture. The aim of this study is an evaluation of the technical efficiency of Czech organic farms and determining the main factors, including subsidies, which affect the technical efficiency of both conventional and organic farms. The Farm Accountancy Data Network Czech Republic (FADN CR) database provides sufficient panel data for this kind of research focusing on types of farming with livestock production. The methodological tool used to achieve the aim of this paper is the parametric stochastic frontier analysis, "True" Random Effects model, supposing farms heterogeneity and time variant determinants of inefficiency. The results of the research verified differences in the technical efficiency of organic and conventional agriculture related both to the different farming methods and to the production conditions. The type of farming and the economic size of farms influence the farms' profitability, economic performance and comparability with conventional farms. The technical efficiency of organic farming is growing over the long term. Farms with growing technical efficiency show a decline in the proportion of operating subsidies to production, irrespective of their classification in quartiles by the technical efficiency estimate.

Keywords: firm heterogeneity; organic farming; panel data; production function; stochastic frontier analysis; technical efficiency

By 31 December 2016, there were 4 243 organic farms (about 9% of agricultural holdings in the Czech Republic) with a total organic acreage of 506 070 ha, which represents a 12.3 % share of the total of agricultural land (MoA 2017). The comparable research has been previously realised to a limited extent, in terms of the included period, selection of holding type, and available data sources. Cechura (2014) or Zakova Kroupova (2016) published an analysis based on FADN data, but the results were limited due to a lack of adequate data of organic farming, including individual owners/natural persons.

The current FADN CR has a representative dataset according to document RI/CC 1750, ex RI/CC 882 (EC 2015), including organic farms, so there is relevant and representative data for our extended research. Therefore, the aim of this paper is an evaluation of the technical efficiency of both Czech organic farms (OF) and conventional farms (CF) and determination of main factors, which affect the technical efficiency (TE) including subsidies using the FADN database for the period of 2011–2016 (FADN CZ database 2017).

Opinions about the meaningfulness and effectiveness of subsidies differ. Efficiency and subsidies were found to be driving forces behind the adoption of organic technology (Kumbhakar et al. 2009). Others hold the view that the subsidies are insufficient, that the organic farmers should be compensated for a loss of profit and environmental services. Comparative analysis was published by Brozova (2010) and Trnkova et al. (2012). An evidence for the influence of environmental subsides on the technical efficiency of the grain farms in Norway has been provided by Kumbhakar et al. (2014). When evaluating policies, it is important for both efficiency and equity reasons to understand

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whether support goes to those it is intended, e.g. farmers with low income in the form of income support or those who provide the required level of environmental or social benefits (Moreddu 2011).

The aim of the research was, therefore, also to assess the impact of subsidies on TE of farms specialised in animal production and to provide a comparison from many aspects including OF/CF and the TE quartiles.

MATERIAL AND METHODS

The method in empirical part is based on Greene (2005) supposing that the "True" Random Effects model (TRE) allows for time-variant technical inefficiency, while the firm (time-invariant) heterogeneity is contained in the time-invariant random intercept. We suppose that both OF and CF technologies use similar agricultural practices in case of livestock types of farming. Farm characteristics as a location in the less favoured area (*LFA*), organic technology, investment subsidies, economic size (*ES*) and type of farming (*TF*) were used as the technical inefficiency (TI) explanatory variables.

Data

The unbalanced panel data for the estimation of the production function was taken from the FADN 2011–2016 period (FADN CZ database 2017). The panel contained the data of 440 farms (114 OF, 326 CF) focusing on farming with livestock production that showed 4 or more observations.

"True" Random Effects model

The methodological tool to achieve the aim was the parametric Stochastic Frontier Analysis (SFA). Debreu (1951) and Farrell (1957) defined the following measure of technical efficiency, known as the Debreu-Farrell measure. Panel data frontier model estimation has been widely used to estimate technical efficiency (Kumbhakar et al. 2014). The econometric results suggest that stochastic frontier models generate lower mean TE estimates than non-parametric deterministic models, while parametric deterministic frontier models yield lower estimates than the stochastic approach (Bravo-Ureta et al. 2007). Stochastic models structured to capture inefficiency that is time invariant (and mixed with firm effects) may lead to very low efficiency estimates, while models in which firm effects are not considered to be part of inefficiency may give high efficiency scores (Kumbhakar et al. 2014). The "True" Random Effects model was used in our research supposing that inefficiency varies over time and at individual farms level (heteroskedastic). SFA is a parametric method whose production boundary is stochastic, i.e. it allows to assume the presence of statistical noise and allows the model, and its behavior, to be constructed according to the inefficiency change over time as a true fixed effects model, assuming that the effect of the inefficiency components are the same for all holdings, or a TRE model, assuming that the impact of the components may vary from one holding to another (Coelli et al. 2005; Cechura 2010). The purpose of these models is to disentangle firm heterogeneity or firm effects from TE.

Coelli et al. (2005) described the Stochastic Production Frontier and Cobb-Douglas Stochastic Frontier model in the form:

$$q_i = \exp(\boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \ln \boldsymbol{x}_i) \times \exp(v_i) \times \exp(-u_i) \quad (1)$$

where q_i represents output of the i^{th} firm; $\boldsymbol{x}_i$ is $K \times 1$ vector containing the logarithms of inputs (deterministic components); $\boldsymbol{\beta}$ is a vector of unknown parameters; v_i captures statistical noise while u_i reflects technical inefficiency. Much of SFA is directed towards the prediction of the inefficiency effects. The most common output-oriented measure of TE is the ratio of observed output to the corresponding stochastic frontier output:

$$TE_i = \frac{q_i}{\exp(\boldsymbol{x}_i' \boldsymbol{\beta} + v_i)} = \frac{\exp(\boldsymbol{x}_i' \boldsymbol{\beta} + v_i - u_i)}{\exp(\boldsymbol{x}_i' \boldsymbol{\beta} + v_i)} = \exp(-u_i) \quad (2)$$

This measure of technical efficiency takes a value between zero and one. It measures the output of i^{th} firm relative to the output that could be produced by a fully-efficient firm using the same input vector. The "True" Random Effects specification by Greene (2005):

$$y_{it} = \alpha + \boldsymbol{\beta}_i' \boldsymbol{x}_{it} + v_{it} - \exp(-u_i) \quad (3)$$

We consider a translog stochastic production frontier defined as follows (Coelli et al. 2005) (Equation 4).

$$\ln q_{it} = \ln f(t, \boldsymbol{x}_{it}; \boldsymbol{\beta}) = \alpha + \sum_{j=1}^{K} \boldsymbol{\beta}_j \ln x_{ijt} + \frac{1}{2} \sum_{j=1}^{K} \sum_{k=1}^{K} \boldsymbol{\beta}_{jk} \ln \boldsymbol{x}_{ijt} \ln \boldsymbol{x}_{ikt} + \boldsymbol{\beta}_t t + \frac{1}{2} \boldsymbol{\beta}_{tt} t^2 + \sum_{j=1}^{K} \boldsymbol{\beta}_{jt} \ln \boldsymbol{x}_{ijt} t + v_{it} - u_{it} \quad (4)$$

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In Equation 4, q_{it} is the output of the i^{th} firm in the t^{th} year; x_{ijt} denotes a n^{th} input variable; t is time trend representing technical change. The output y_{it} is the logarithm of the total output, FADN standard results variable (EC 2015), deflated by the price index of agricultural producers (2010 = 100, Eurostat (2018)). Vector of inputs contains four production factors x_1 – land, x_2 – livestock units (*LU*), x_3 – annual working units (*AWU*) as labour input and x_4 – material deflated by the price index of agricultural inputs presented by intermediate consumption, which covers part of capital costs (machinery and building current costs, energy, contract work). Since all the variables are divided by their geometric mean, the fitted parameters represent production elasticities (Cechura 2014). Time-trend variables are represented by t (time variable expressing technical change) and t_2 (the dynamics of change over time). Table 1 presents descriptive statistics for the variables included in the model for both farming systems.

The second set of variables represents the explanatory variables for the technical inefficiency variance function (u_{it} in Equation 2). Technical inefficiency (TI) components were set up by dummies (1/0): *dLFA*, *dOrganic*, *d*405 (subsidies on investments), *TF* and *ES* according to FADN typology *dTFMix*, *dTFMilk*, *dTFCattle*, *dES*4 (1 = small, 2 = middle, 3 = large, 4 = very large). Manevska-Tasevska et al. (2013), used the explanatory variables classified in four groups, time-trend variable, farmer and farm characteristics, grants and subsidies, and environmental condition/location (including *LFA*, organic and investment support scale). The inefficiency term was assumed to have an exponential distribution. Based on the assembled model, STATA sfpanel command was used. Estimation of TE score was then performed for each observation of the survey period via $E\{\exp(-u|\varepsilon)\}$ (Belotti et al. 2013).

RESULTS AND DISCUSSION

Parameter estimates

The estimation of the production function parameters is given in Table 2, specifying the first and the second order parameters. The estimated values of the asymmetric technical inefficiency component (u) are in the column of other parameters, the symmetrical component (v) of the statistical noise (*vsigma*) did not enter the model separately. The estimated production elasticities satisfy the criterion of quasi-concavity

Table 1. Description of variables, CF (0) and OF (1)

Organic		2011	2012	2013	2014	2015	2016	2011–2016	2011–2016 SD	min	max
Total output (,000 EUR)	0	1 481	1 546	1 565	1 650	1 520	1 541	1 551	1 746	5	11 479
	1	101	111	113	113	118	122	113	166	6	1 198
Land (ha)	0	950	947	938	930	928	936	938	922	2	5 980
	1	243	240	240	243	238	226	239	348	14	1 958
Livestock units	0	503	497	496	501	506	494	500	492	4	2 348
	1	106	108	104	110	117	113	110	157	5	1 052
AWU	0	30.4	30.1	29.7	29.1	28.6	28.4	29.4	30.2	0.5	163.4
	1	4.6	4.6	4.6	4.6	4.6	4.5	4.6	5.7	0.8	35.1
Material (,000 EUR)	0	1 090	1 131	1 188	1 220	1 185	1 214	1 172	1 293	4	8 939
	1	115	117	122	117	117	113	117	178	8	1 160
Number of observations	0	326	326	326	325	317	309	1 929	–	–	–
	1	114	111	111	114	113	109	672	–	–	–

CF – conventional farms; OF – organic farms; *AWU* – annual working units; SD – standard deviation

Source: own calculations

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Table 2. Estimation of production function parameters – TRE (“True” Random Effects) model results

Y	Coefficient	Std. error	*z*	*p* > |*z*|
First-order parameters				
x_1	–0.029	0.030	–1	0.338
x_2	0.193	0.026	7.4	0.000
x_3	0.130	0.025	5.11	0.000
x_4	0.745	0.029	25.8	0.000
t	0.070	0.007	9.65	0.000
Second-order parameters				
x_4 sq	0.110	0.059	1.85	0.065
x_1 sq	–0.059	0.047	–1.2	0.214
x_2 sq	0.149	0.060	2.5	0.012
x_3 sq	–0.016	0.053	–0.3	0.762
$x_{4–1}$	0.181	0.086	2.09	0.036
$x_{4–2}$	–0.267	0.083	–3.2	0.001
$x_{4–3}$	–0.099	0.084	–1.2	0.235
$x_{1–3}$	0.109	0.096	1.13	0.258
$x_{1–2}$	–0.113	0.081	–1.4	0.161
$x_{2–3}$	0.023	0.084	0.27	0.786
t_2	–0.023	0.002	11.7	0.000
$x_{4\_}t$	–0.019	0.005	–3.7	0.000
$x_{1\_}t$	0.012	0.004	2.68	0.007
$x_{2\_}t$	0.007	0.005	1.47	0.143
$x_{3\_}t$	0.005	0.004	1.21	0.225
_cons	0.029	0.029	1.02	0.308
Other parameters				
Usigma				
dLFA	0.035	0.183	0.19	0.847
dOrganic	0.866	0.178	4.87	0.000
dES4	–0.711	0.074	–9.56	0.000
dTFMix	–0.451	0.311	–1.45	0.147
dTFMilk	–0.337	0.322	–1.05	0.295
dTFCattle	1.066	0.268	3.97	0.000
*d*405	–0.310	0.166	–1.87	0.062
_cons	–2.744	0.357	–7.68	0.000
Vsigma				
_cons	–5.152	0.073	70.5	0.000
Theta				
_cons	0.258	0.011	23.8	0.000
E(*sigma_u*)	0.130	–	–	–
Sigma_v	0.076	0.003	27.4	0.000
Lambda	1.714	–	–	–

x_1 – land; x_2 – livestock units (*LU*); x_3 – annual working units (*AWU*) as labour input; x_4 – material deflated by the price index of agricultural inputs presented by intermediate consumption; sq – squared; t – time variable expressing technical change; t_2 – dynamics of change over time; *dLFA* – less favoured area; *dOrganic* – organic technology; *d*405 – subsidies on investments; *dES*4 – economic size; *dTFMix* – mixed production; *dTFMilk* – dairy production; *dTFCattle* – cattle breeding; *TF* – type of farming

Source: own calculations

and partly monotonicity (Sauer et al. 2006), i.e. the elasticities are positive for x_2, x_3 and x_4 with the diminishing marginal productivity except of x_1.

Total output is significantly affected by material inputs (Newman and Matthews 2006). If the material changes by 1%, total output changes by 0.745%. Elasticity of inputs suggests that the effect of land (x_1 –0.029) on production is negative, connected with extensive land use in OF and cattle breeding in general, but statistical significance has not been demonstrated so under certain circumstances, this value may be acceptable and the model, as such, may serve the needs of estimating TE. The statistically significant negative influence of land was found for farms of the United Kingdom as well. The non-significant positive effect was identified for farms in Spain and Ireland (Latruffe et al. 2016).

Significant at $p < 0.01$ the impact of *LU* (x_2 0.193) and *AWU* (x_3 0.130) representing labour elasticity and material (x_4 0.745) proved to be statistically significant in our research. The sum of elasticity for the average holding based on the model is greater than 1 indicating an increasing return to scale. The technical change affects the production positively and is statistically significant (t 0.07), the dynamics of the technical change over time decreases (t_2 –0.023). The technological progress, given by values of estimated parameters $\boldsymbol{\beta}_{jt}\ln \boldsymbol{x}_{ijt}\, t$, was land demanding ($x_{1\_t}$ 0.012) and material slightly saving (x_{4_t} –0.0186). From other parameters assumed to affect inefficiency, the positive influence of OF (*dOrganic* 0.866) through the heteroscedasticity (variance of technical inefficiency) was found. It means that this factor is negative to TE and statistically significant. The negative effect on the technical inefficiency (TI) is based on the economic size group factor (*dES*4 –0.711) i.e. the TI decreases with the growing size of the farm. In addition, the statistically significant positive impact on the TI of cattle breeding farms (*dTFCattle* 1.066) was demonstrated, as opposed to mixed and dairy production (*dTFMix* –0.451, *dTMilk* –0.337), but was not classified as statistically significant. Investment subsidies (*d*405 –0.310) had a negative effect on TI with low statistical significance ($p < 0.1$). Contrary to this, Lakner (2009) described a negative effect of investment subsidies to a farm’s efficiency score.

The parameter λ, as a *sigma_u* and *sigma_v* ratio, is more than one and so it can be assumed that the variation of inefficiency parameters (*sigma_u*) is more significant than the variation in statistical noise (*sigma_v*).

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Technical efficiency development

There are a number of studies comparing the TE of OF and CF. Some studies based on SFA suggest that OF are more technically efficient than CF (Tzouvelekas et al. 2001; Oude Lansink et al. 2002), but other studies suggest the opposite (Serra and Goodwin 2009). The technical efficiency of CF farms (0.918 on average for the period) significantly outstrips the efficiency of the OF farms (0.685) in our research, so their performance can be assessed as more efficient. Nonetheless, there is a slight decrease in efficiency in CF over the period (–1.3%) under review in contrast to the trend in OF (2.5%). According to Madau (2007), the estimated TEs for conventional and organic practices are, on average, 0.902 and 0.831, respectively. This indicates that OF are less efficient than CF, relative to their specific frontier technology. However, it does not indicate that CF are more efficient than OF to the same degree, because these two practices are situated on different technological frontiers. It only implies that CF operate closer to their specific frontier than OF.

On the other hand, organic farms from our research even with a lower TE show consistent performance over the period under review and in the last year there was a significant improvement, which corresponds to the results and conclusions presented in the FADN CR results (Hanibal 2017). TE average of the Czech OF according to *ES* is similar; 0.651, 0.699, 0.694, and 0.710 for small, middle, large, and very large farms, respectively. The type of farming influences the TE significantly at levels 0.923, 0.759, 0.598, 0.823, and 0.685 for dairy, sheep and goats, cattle, mix, and all farms, respectively (Figure 1). Our results are relevant to earlier studies on the average level of TE. Cechura (2010) found that the average level of TE is around 90%, considering that TE is an important determinant of the competitiveness of Czech agricultural holdings. Zakova Kroupova (2016) reported the change in profitability as positive in the analysed period, and slightly higher for dairy farms than for mixed farms. The average TE of dairy farms was 93.77%, with the standard deviation (SD) at a level of 2.87%. Mixed farms were almost as technically efficient as the dairy farms (average TE of 93.83%, SD of 2.68%). The distribution of TE was therefore narrow for both types of farms (Zakova Kroupova 2016).

Kostlivy et al. (2017) stated that the group of organic farms (representing of the sample of 69%) showed an improvement of total productivity by 3.17%, mainly due to technical efficiencies with a growth of 2% in the period of 2011–2015.

Technical efficiency estimates obtained from our frontier specification for the period of 2011–2016 show TE average for dairy OF 92.32% (SD 0.095) and for mix *TF* 82.25% (SD 0.192). TE mean is similar for CF dairy and mix *TF* at level 94.9% (SD 0.051) and 90.6% (SD 0.109), respectively. The lower SD of dairy farms suggests greater homogeneity. Analysis of the European dairy farm sector concluded that milk farms show a small scope for improving efficiency using their own technical input. These findings suggest that the sizes of the farms are on average supra-optimal and should be reduced to reach the optimal scale (Madau et al. 2017).

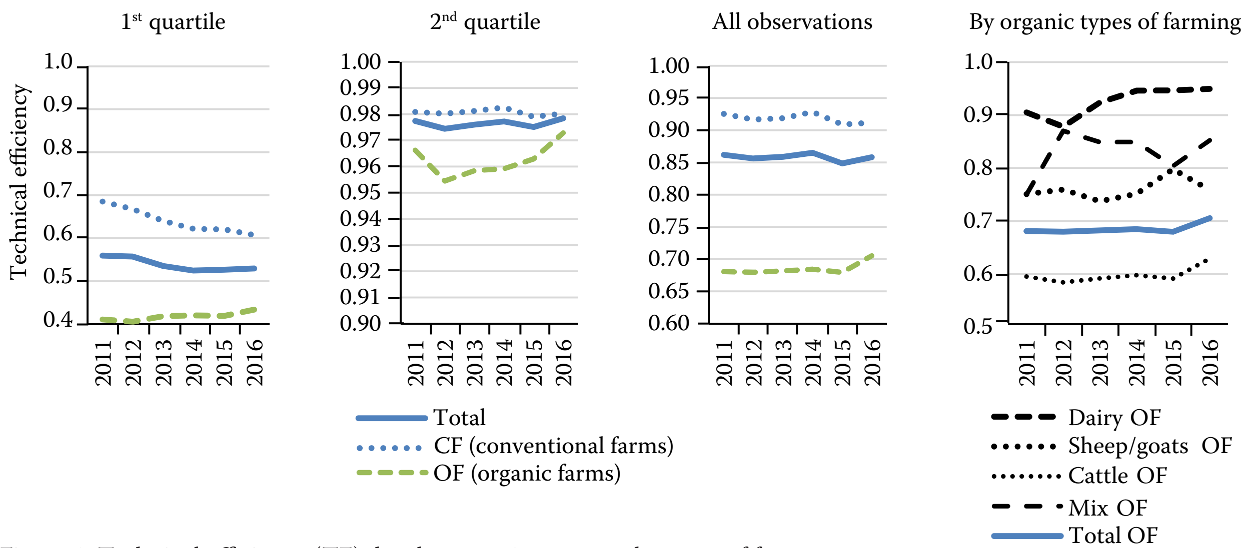

Figure 1. Technical efficiency (TE) development in separated groups of farms

Source: own calculations

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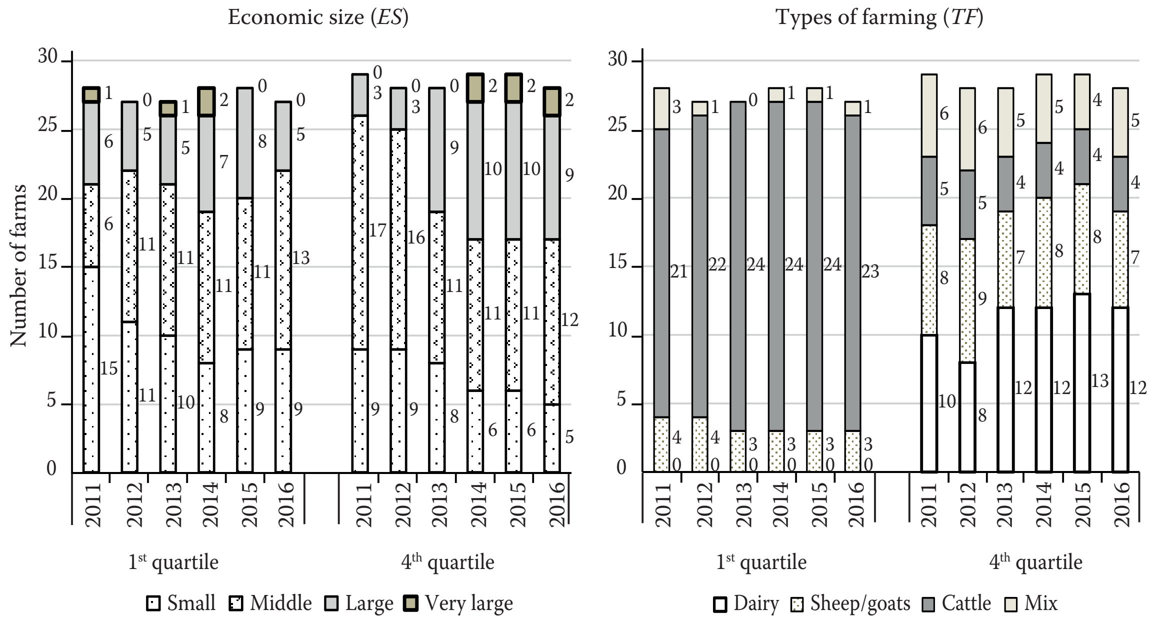

Figure 2. Number of organic farms in the 1st and 4th quartile of technical efficiency (TE) according to economic size groups (*ES*) and types of farming (*TF*)

Source: own calculations

Quartile classification is based on the estimated TE of each observation in the year. Quantitative representation of organic farms in the 1st and 4th quartile of technical efficiency according to types of farming and economic size groups is in Figure 2.

Descriptive statistics of technical efficiency, the input-output variables and the efficiency determinants variables are displayed in Table 3. Average TE of successful CF and OF in the 4th quartile is similar (0.98 and 0.96, respectively), but the lower SD of CF 4th quartile suggests greater homogeneity. Year-on-year TE change index (*te_LAG*) diminished in both 1st quartiles (CF as well as OF) and increased by 4.8% in the group of OF and only by 0.6% in CF farms in the 4th quartile.

Farms in the 4th quartile of CF and OF showed similar values of *LU* (59.9 and 55.9, respectively) as well as *AWU* (3.86 and 3.69, respectively). Farms in the 4th quartile of CF produced higher crop output (788 EUR/ha) than other groups (in average 119–272 EUR/ha). All groups of farms showed a similar proportion of total production except the OF 4th quartile where the higher share of livestock and other output per hectare was found. The ratio of livestock output per *LU* was on the same level in groups of the 4th quartile in CF and OF farms (1 461 EUR/*LU* and 1 453 EUR/*LU*, respectively). The ratio in farms of 1st quartile was lower (513 EUR/*LU* and 345 EUR/*LU*, respectively).

Farm Net Value Added (FNVA) per hectare was higher in the 1st quartile of OF (254 EUR/ha) than CF (212 EUR/ha) group thanks to higher subsidies and by 10% higher in the 4th quartile in CF (824 EUR/ha) than in OF (749 EUR/ha) farms, which agrees with Doucha et al. (2012) that, particularly, very large farms with extensive cows breeding on permanent grassland are over supported and realise rents.

The economic size of farms does not have a significant influence on the economic results in OF. Farms in the 1st and the 4th quartiles of TE have on average similar *ES* (6.3 and 6.5, respectively). That is the opposite to conventional agriculture where TE of the 1st quartile farms represent the middle economic size group, and the 4th quartile farms are mainly large and very large (*ES* average 9.8). Farms in the first quartile according to TE are mainly based on cattle *TF*, and there is no dairy *TF*. On the other hand, the 4th quartile of TE is presented by 1/3 dairy (the most efficient *TF*), 1/3 sheep and goat, and the remaining third consists of mixed and cattle *TF*.

The impact of subsidies, as one of the researched factors, was examined in a separate step through the regression analysis. The highest share of subsidies on farm output was proved in the OF 1st quartile (Table 3). The impact of Single Area Payment Scheme (*SAPS*) subsidies has not been demonstrated. The impact of *LFA* and agri-environmental support (*AES*)

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Table 3. Descriptive statistics – output diversity and efficiency determining variables for all, CF, OF and CF/OF in the 1st and the 4th quartiles

		All	CF	OF	CF		OF	
		n = 2 601	n = 1 929	n = 672	1 quartile	4 quartile	1 quartile	4 quartile
Technical efficiency (TE)	average	0.858	0.918	0.685	0.642	0.981	0.418	0.962
	standard deviation	0.175	0.108	0.211	0.126	0.005	0.074	0.029
Year-on-year TE change index (*te_LAG*)		1.008	0.999	1.033	0.930	1.006	0.924	1.048
LFA (1.2.3)		2.00	1.86	2.40	2.33	1.57	2.54	2.25
LU/100 ha		59.4	62.4	50.9	65.4	59.9	44.4	55.9
AWU/100 ha		3.54	3.78	2.85	4.34	3.86	2.68	3.69
dLFA (1/0 *LFA* yes/no)		0.750	0.688	0.927	0.949	0.501	0.964	0.848
Investment subsidies (1/0 yes/no)		0.169	0.184	0.128	0.041	0.172	0.085	0.111
Livestock output/total output (share)		0.509	0.492	0.558	0.501	0.478	0.532	0.640
Other output/total output (share)		0.065	0.063	0.071	0.044	0.065	0.036	0.086
Crop output/total output (share)		0.426	0.445	0.371	0.455	0.457	0.433	0.274
Total subsidies excl. on investment/total output (share)		0.609	0.335	1.396	0.813	0.214	2.219	0.596
Total subsidies excl. on investment/total inputs excl. wages (share)		0.473	0.331	0.883	0.551	0.278	0.958	0.635
Total inputs excl. wages/total output (share)		1.113	0.966	1.535	1.485	0.786	2.364	0.919

CF – conventional farms; OF – organic farms; n – number of observations; *LU* – livestock units; *LFA* – less favoured area; *AWU* – annual working units; excl. – excluding

Source: own calculations

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subsidies corresponds to the *dLFA* factor (dummy variable). *AES* per hectare were almost 4 times higher in the 1st quartile of CF than in the 4th quartile and subsidies in the 1st quartile of the OF group were at 123% of the 4th quartile. The lower share of *AES* and *LFA* subsidies on total subsidies excluding investment in CF compare to OF is an evidence of farming in mountain areas mainly with permanent grass.

Estimated TE for all the observations and their correlation to the classification according to their economic size, type of farming, LFA and level of subsidies (per ha) was tested using Spearman's rank correlation coefficient and Kendall-tau test. Tau-b range from –1 (perfect inversion) to +1 (perfect agreement), a value of zero indicates the absence of association. Madau (2007) found that assignment to a LFA is the factor that mainly affects TE in both CF and OF.

A positive effect on TE was found for dairy *TF* (tau-b = 0.355 for OF, 0.177 for all farms) and *ES* (tau-b 0.251 for all farms, not significant for OF). Negative dependences were found for OF dummy (tau-b –0.372 for all farms), *LFA* localisation (tau-b –0.3194 for all farms, –0.1231 for OF), cattle *TF* (tau-b –0.5117 for all farms, –0.442 for OF), and land size (tau-b –0.1263) for OF. At both OF and all farms level, the negative relation between TE and *AES* or *LFA* subsidies was calculated, which confirms the results of Lakner (2009) and Lakner et al. (2011) about the negative impact of subsidies on the production and TE in OF. According to Manevska-Tasevska et al. (2013), dependence on subsidies has a negative influence on the TE at all farm specialisations. Milk farms are significantly less dependent on subsidies, whereas specialisation in cattle production increased farm dependence on subsidies in Sweden. The hypothesis that the actual level of the subsidy discourages organic farmers from rational behaviour and implicates their dependence on state support was not confirmed.

Statistical tests of the impact of individual factors on TE were carried out for all farms in our research. A statistically significant positive effect ($p < 0.01$) was demonstrated for dairy farms, according to *ES*, the FNVA and the depreciation values per hectare. However, statistically significant values of depreciation per *LU*, *SAPS*, *LFA* and *AES* per *LU* show very low regression coefficients. The statistically significant negative impact ($p < 0.01$) was on the labour intensity (*AWU*/ha), the share of *SAPS* subsidies on total output, the share of production costs and the inclusion of the holding in the production focus of cattle *TF*. The negative impact of *LFA* subsidies has a low regression coefficient of zero. A negative, but not statistically significant, effect is the assessment of the share of *AES* on total output. The negative impact of subsidies on *LU*s (–0.00000116) can be taken as zero.

CONCLUSION

This study analyses the technical efficiency of livestock types of farming in the Czech Republic using unbalanced panel data FADN with 2 601 observations from 440 farms over 6 years (FADN CZ database 2017). Technical efficiency is estimated using stochastic translog production function with the "True" Random Effects specification. Assuming that, in this model, the impact of the components may vary from one farm to another and the variables representing heterogeneity are incorporated into the mean of the exponential distribution of the inefficiency term. The technical efficiency and impact of different factors, such as economic size, type of farming, localisation and presence of investment subsidies, were investigated. These can be treated as factors of heterogeneity and their impacts on technical inefficiency was evaluated. The empirical results confirm that localisation, economic size, type of farming and organic agriculture influence the TE of livestock types of farms.

The negative value of the land input parameter, in the model for all farms, corresponds with extensive land use in livestock types of farming in general. The negative influence of organic farming and cattle type of farming to the TE was proved. The technical inefficiency decreases with the growing size of the farm. The TE of conventional farms significantly outstrips the TE of the organic farms. Nonetheless, there is a slight decrease in the TE over the period, opposite to the trend in organic farming in the researched period. We may also conclude that to a certain level the *LFA* and *AES* subsidies have a negative and statistically significant impact on the TE. The effect of the *SAPS* subsidy was not proved. Subsidies on investments which anticipate farm modernisation, positively contribute to the decline of technical inefficiency. The recipients of the highest subsidies amount are mostly small farms in 1st quartile of technical efficiency TE. These findings could provide an important message about the setting of *AES* and *LFA* subsidies. Our results confirmed, as did many other studies, that subsidies supporting investment and innovation activity positively influence overall competitiveness by increasing technical efficiency.

Differences in the TE of organic and conventional agriculture are related both to the different farming

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methods and to the production conditions. Granted *LFA* and *AES* subsidies compensate these differences, and for technical efficiency, they are decisive but with negative impact. Type of farming and economic size of farms influence the farms' profitability, economic performance and comparability with conventional farms. The main indicator of profitability (farm net value added per *AWU*) confirmed that subsidies are an important part which compensate farming methods and to the production conditions for organic. *F*arms with growing TE show a decline in the proportion of operating subsidies to production, irrespective of their classification in quartiles by the TE estimate.

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