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Drivers of farm performance in Czech crop farms

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Abstract: When analysing drivers affecting the farm performance, the presence of different technologies should be taken into account. We assume that the technology used by crop farms is not the same for all producers and therefore we use latent class model to identify technological classes at first. Class definition is based on multidimensional classification and determination of indices given by the values of individual components. The principal components analysis is applied to estimate significant and robust weights for the index components. FADN (Farm Accountancy Data Network) database, Czech crop farms data from 2005 to 2017 were used and three groups of technology classes of farms were identified with a determinant influence of the structure index and localisation. The other indices characterise sustainability, innovation, technology, diversification, and individual characteristics. Three distinct classes of crop farms were found, one major class and two minor classes. Family driven farms are usually smaller farms in terms of acreage. Highly sustainable crop farms are most likely located in lower altitudes and not in less-favoured areas. Innovative farms are also likely to be more productive. The results indicate that agricultural production farms with a more sustainable way of farming are most likely to be more productive.

Keywords: farms heterogeneity; latent class model; panel data; ; principal component analysis; production function; stochastic frontier analysis; technical efficiency

The analysis of farm technical efficiency (TE) has interested researchers for the past decades, and several methodologies for frontier estimation have been developed and empirically applied in many economic fields, including agricultural economics (Cillero et al. 2019). Stochastic production frontier functions have been increasingly used to measure efficiency of individual producers. Estimation of these functions rests on the assumption that the underlying production technology is common to all producers (Orea and Kumbhakar 2004). The assumption that farms operate under a homogenous technology is widespread (Hockmann and Pieniadz 2008; Alvarez and del Corral 2010; Cechura 2010; Cillero et al. 2019). However, farms may use different technologies. In such a case, estimating a common frontier function may not be appropriate and the estimate of the underlying technology may be biased (Orea and Kumbhakar 2004). The results of Baráth and Fertő (2015) suggest that technological heterogeneity plays an important role in Hungarian crop farms, which are traditionally assumed to use homogeneous technologies. Many studies concluded that if technology heterogeneity was not considered when estimating technical efficiency, results could be misleading (Cillero et al. 2019).

The presence of different technologies means that empirical analyses of technical change (TCH), and its drivers and effects, are more complex than calculations typically modelled by shifts and twists in a common production frontier or function (Sauer

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and Morrison 2013). Furthermore, unless technological differences are not taken into account in the estimation, technical efficiency (TE) scores may be underestimated and the effects might be inappropriately labelled as inefficiency (Orea and Kumbhakar 2004; Baráth and Fertő 2015). Several authors attempt to account for technology heterogeneity. First, it is common to consider a single specific exogenous characteristic in order to divide the sample and estimate separated frontiers for each subsample. However, firms usually employ diverse technologies for a variety of reasons (Tsionas 2002). Therefore, the use of a single characteristic of the production technology might be challenging when heterogeneity is likely to arise from more than one factor, leading to an arbitrary or incomplete division of the sample (Alvarez et al. 2012; Sauer and Morrison 2013).

There are two possible ways of identifying different technological groups and their production frontiers in one or two stages. First, the sample observations are classified into several groups. This classification is based either on some *a priori* sample separation information (e.g. ownership, location) or on applying cluster analysis to variables such as output and input ratios. In the second stage, separate analyses are carried out for each class/sub-sample (Orea and Kumbhakar 2004). The technological specification used for empirical analysis of production technologies and TCH should accommodate both different points on a production frontier and separate frontiers for different farms, which can lead to using a latent class model (LCM) with multiple characteristics acting as separating variables (Orea and Kumbhakar 2004; Greene 2005; Sauer and Morrison 2013). An LCM assumes that there is a finite number of structures (classes) underlying the data (Alvarez and del Corral 2010). Statistical tests Akaike information criterion/Schwarz and Bayesian information criterion (AIC/SBIC) were applied to determine the number of classes. The preferred model will be that for which the value of the statistic is lowest.

Recent studies have identified some of the potential factors affecting TE, including farm size, farm organisation, and policy measures. Baráth and Fertő (2015) investigated technological heterogeneity in Hungarian crop producing farms, differentiating a typical dual structure, assumed that the technology used by crop farms is not the same for all producers and analysed the effect of unobserved technological differences using an LCM to identify technological classes at first. The results revealed that there is lower chance to increase performance through TE improvement than had been expected.

Apart from stochastic frontier analysis (SFA), latent class has also been applied to average production functions. Sauer and Morrison (2013) employ a transformation function in the latent class framework, where different technologies are classified based on production intensity. The full-model specification and random effects based estimator can be applied for defined technology classes in a panel form (Greene 2005; Sauer and Morrison 2013).

The aim of this paper was to analyse a panel data of crop production farms in the Czech Republic. Farm Accountancy Data Network data (FADN CZ Database 2018) for the period 2005 to 2017 was used. We combined the latent class stochastic frontier model with the complex time decay model to form a single-stage approach that accounts for unobserved technological differences to estimate efficiency and the determinants of efficiency. In other words, in our research a single stage method was used in two steps.

We were interested in the efficiency of each group, the LCM was applied in a stochastic frontier framework (Greene 2005). To identify groups of technology classes, seven indices and their components were used. We suppose heterogeneous technology is used in Czech crop farming with the aim to find out technology class groups and for each group class productivity and SFA estimates. We are concerned with the effects of given factors (indices based on the values of individual components) on the TE and TCH.

MATERIAL AND METHODS

Applied methodology. The empirical analysis was applied in several steps: *i*) different indices for farms inclusion into groups with different technologies were defined; *ii*) the principal components analysis (PCA) to calculate index scores was run; *iii*) technologies and classes using LCM approach were estimated; *iv*) TE level per class using SFA was estimated; *v*) results – per class interpretation. For analysis and production function estimation MS SQL Server and Stata 15.0 software were used.

For the empirical analysis, the whole dataset of farms was divided into three categories. The PCA multivariate method was used to estimate weights for the index components (Afifi et al. 2012). The objective of PCA is to find unit-length ($L'L = I$) linear combinations of the variables with the greatest variance. The first principal component has maximal overall variance. The second principal

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component has maximal variance among all unit-length linear combinations that are uncorrelated to the first principal component (Jackson 2003).

Separating components for multi-dimensional indices as elements of class identification. The sample observations for LCM are based on multidimensional classification and determination of indices given by the values of individual components (PCA). We assume that farms differ by several characteristics grouped into 7 indices consisting of components, i.e. variables (Table 1).

Using these indices and their components, the sample observations are classified into several groups. The values of indices for PCA were calculated as *z*-scores to solve the problem of different expressions of values of different components (i.e. share of family work *vs.* share of land rented or form of ownership):

$$z = \left(x_i - x_{mean}\right) / x_{stdev} \tag{1}$$

where: x_i – i^{th} observation of x; x_{mean} – arithmetic mean of x; x_{stdev} – standard deviation of x.

To empirically identify and estimate heterogeneous classes of observations and separate the data into multiple technological classes (groups or categories), the latent class structures (LCM) was applied.

To account for heterogeneity, Orea and Kumbhakar (2004) advocate using a single-stage approach, i.e. a latent class stochastic frontier model that combines the stochastic frontier approach with a latent class structure. Moreover, authors proposed a model that avoids the problem of testing time-invariant inefficiency. However, in this paper the two-steps method was used. Firstly, the sample observations were classified into several groups, and secondly, separate analyses for each class were performed. The two-step approach was used to provide transparent analysis of different classes and to run descriptive characteristics of farms (observations) included in different groups. For the estimation of technical efficiency, stochastic frontier approach was used.

SFA is a parametric method which production boundary is stochastic, i.e. it allows to assume the presence of statistical noise and lets the model, and its behavior, to be constructed according to the inefficiency change over time. The model was estimated in the form of trans logarithmic production function.

The panel-data-related specification of the model is (Coelli et al. 2005):

$$\begin{aligned} \ln_{y_{it}} = \boldsymbol{\alpha} + \sum_{j=1}^{K} \boldsymbol{\beta}_j \ln \boldsymbol{x}_{ijt} + \frac{1}{2}\sum_{j=1}^{K}\sum_{k=1}^{K} \boldsymbol{\beta}_{jk} \ln \boldsymbol{x}_{ijt} \ln \boldsymbol{x}_{ikt} + \\ + \boldsymbol{\beta}_t \boldsymbol{t} + \frac{1}{2}\boldsymbol{\beta}_{tt}\boldsymbol{t}^2 + \sum_{j=1}^{K} \boldsymbol{\beta}_{jt} \ln \boldsymbol{x}_{ijt}\boldsymbol{t} + \boldsymbol{v}_{it} - \boldsymbol{u}_{it} \end{aligned} \tag{2}$$

where: y_{it} – the output of the i^{th} firm in the t^{th} year; x_{ijt} – a n^{th} input variable; t – time trend representing TE.

Stochastic frontier analysis – "true" random effects model (TRE). In this paper we focused on measuring both productivity and unobserved inefficiency (based on a frontier specification) for each class separately. The TRE model was used in our research supposing that inefficiency varies over time and at individual farms level (heteroskedastic).

Table 1. Indices and components for farm classification

Index	Definition
Production structure (1)	family/hired labour ratio; UAA; form of ownership (1: self-employee, 2: legal person, 3: cooperative)
Sustainability (2)	chemicals use per ha; organic (probability); AEO subsidies per ha
Innovation/cooperation/commercialisation (3)	net investment ratio (per total assets); share land rented; biofuel production (probability)
Technology (4)	capital/labour ratio per hour; material per ha; labour per ha; input services share
Diversity (5)	Herfindahl index; livestock production (probability); other output (probability)
Individual (6)	age (years); education (1: primary, 2: secondary, 3: high)
Location (7)	LFA subsidies per ha; altitude (1: < 300, 2: 300–600, 3: > 600); LFA classification (1: not to 3: severely disadvantaged)

LFA – less favourable area; AEO – agri-environmental; UAA – utilised agricultural area
Source: Sauer (2018)

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In the fixed-effects model it is assumed that the inefficiency term is fixed and the correlation with regressors is allowed. In the random effects model the opposite situation is considered: the $\boldsymbol{u}_i$ are randomly distributed with constant mean and variance but are assumed to be uncorrelated with the regressors and the $\boldsymbol{v}_{it}$. The random effects specification assumes that the firm specific inefficiency is the same every year, i.e. the inefficiency term is time invariant. In this form the model absorbs all unmeasured heterogeneity in $\boldsymbol{u}_i$. To avoid TRE model limitations, Greene (2005) proposed a TRE model that is as follows:

$$\boldsymbol{y}_{it} = \boldsymbol{\alpha} + \boldsymbol{\beta}'\boldsymbol{x}_{it} + \boldsymbol{w}_i + \boldsymbol{v}_{it} - \boldsymbol{u}_{it} \tag{3}$$

where: $\boldsymbol{w}_i$ – the random firm specific effect; $\boldsymbol{v}_{it}$ and $\boldsymbol{u}_i$ – the symmetric and one-sided components.

Since heterogeneity of farms has been proven by many studies (Matulova and Cechura 2016), the TRE model was chosen as an appropriate tool assuming that the impact of the components may vary from one farm to another (Coelli et al. 2005).

Data. The unbalanced panel data was taken from the FADN CZ Database (2018) for the period 2005–2017. The panel contained the data of 506 farms focusing on crop production with 5 or more observations. Descriptive statistics of Czech crop farms, full sample (1st and final year), are in Table S1 and Supplementary Material S1 in electronic supplementary material (ESM); for ESM see the electronic version.

The first set of variables includes basic variables (output and inputs) used for production function estimation. The following variables were used in the analysis: Output (y), Land (x_1), Labour (x_2), Capital (x_3), Material (x_4), and Chemicals (x_5). Output is represented by the total output of crops (y_{it}), deflated by the price index of agricultural producers (2010 = 100) (Eurostat Archive 2017). Land as utilised agricultural area (UAA) is expressed in ha, Labour[1] in annual working units (AWU). Capital is presented as net worth [(total assets – total liabilities) + contract work + depreciation]. Material is intermediate consumption excluding feed for grazing livestock and other livestock inputs. Chemical variables are represented by crop protection costs. Input variables were deflated by the price index of agricultural inputs. All variables were normalised with respect to the geometric mean and expressed in natural logarithms.

The second set of variables represents the explanatory variables for the technical inefficiency (TI) variance function (u_{it}; Equation 2). TI components were set up by altitude, less favoured area (LFA) category, form of ownership (values range in Table 1), investment subsidies dummy (1/0, yes/no), agri-environmental subsidies (AEO) dummy (1/0), LFA subsidies dummy (1/0), crop protection dummy (1/0), unpaid labour dummy (1/0), economic size (ES) category (1: 3–4, 2: 6–8, 3: 9–11, 4: 12–14), UAA (ha) group (1: 4–83.9, 2: 84–195, 3: 195.1–619.9, 4: 620–6 842), environmental subsidies per ha group (1, 2, 3, 4), LFA subsidies per ha group (1, 2, 3, 4), material costs per total output of crops group (1, 2, 3, 4), age (years) group (1: 18–35, 2: 36–53, 3: 54–71, 4: 72–87).

Other inefficiency variables tested (but not used) were livestock units per ha, education (1: primary, 2: secondary, 3: higher), organic farming dummy (1/0), organic farming category (1, 2, 3, 4), AWU group (1, 2, 3, 4), AWU per ha group (1, 2, 3, 4), share land rented group (1, 2, 3, 4), capital/labour ratio group (1, 2, 3, 4).

RESULTS AND DISCUSSION

Crop production farms represent 30% of farms of Czech Republic using 35% of total agricultural land (CSO FSS 2016). The dataset used in the latent class panel and a trans log production function was based on the estimation routine offered by the econometric software Stata (version 15).

Three distinct classes of crop farms can be identified for the period 2005–2017, one large class and two minor classes. Class 1 covers about 14% of all crop farms, Class 2 about 60% and Class 3 of about 26% of all farms. This classification is based on some *a priori* sample separation information (Table 1). For Czech crop farms, three distinct technology classes appear from the model estimates (Table 2).

The characteristics of the three estimated crop farm classes are summarised in Table 3 and Figure 1 with respect to the various indices used to identify the class membership of individual crop farms. Descriptive statistics by class is in Table S2 in electronic supplementary material (ESM); for ESM see the electronic version.

Family farms, characterised by unpaid labour, family labour share, and form of ownership, are generally smaller in terms of hectarage (structure index for Classes 1 and 2). Highly sustainable crop farms are most likely at lower altitudes and not in LFA (Class 3). Farms with an above-average innovation

[1]Paid/unpaid labour ratio is used when defining classes

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Table 2. Characteristics of Czech crop farms, by class

	Class 1 (14%)*	Class 2 (60%)	Class 3 (26%)
Number of observations	626	2 644	1 159
Prior probability of class membership	0.1731	0.5991	0.2276
Posterior probability of class membership	0.1413	0.5969	0.2616
Productivity level (EUR per year)	193 222	217 647	1 611 540

*(%) of farms sample
Source: Authors' calculations based on the FADN CZ 2005–2017 data (FADN CZ Database 2018)

Table 3. Class identification – mean values indices, Czech crop farms

Indices mean values*	Class 1 (14%)**	Class 2 (60%)	Class 3 (26%)
Structure	–0.3294	–0.3341	0.94
Sustainability	–0.1032	–0.0721	0.2202
Innovation/cooperation/commercialisation	–0.0076	–0.1091	0.2531
Technology	–0.2086	–0.0436	0.2121
Diversity	0.0464	–0.2614	0.5713
Individual	–0.2087	–0.1206	0.5332
Location	1.4915	–0.3099	–0.0986

*At class means, scaled values; **(%) of farms sample
Source: Authors' calculations based on the FADN CZ 2005–2017 data (FADN CZ Database 2018)

index are also more likely to be more productive (Table 4), which is in accordance with the results of Alvarez and del Corral (2010). Hockmann and Pieniadz (2008) also revealed the existence of an unobserved firm-specific production factor in addition to land, capital, labour and intermediate input. This factor captures the effect of environmental conditions and covers differences in factor qualities such as climate condition, soil fertility, and human capital, including management skills.

Class 1 farms are most likely to be in LFA and higher altitude. The share of unpaid labour force is higher in Classes 1 and 2 compared to Class 3 and is related to the prevailing form of ownership, education, and a lower share of rented land. Class 3 farms are the most productive and usually operated by a legal person. These farms show the highest share of rented land and a higher net investment ratio than the average crop farm. Managers of these farms are older, with higher education than average, and farms are more likely to be

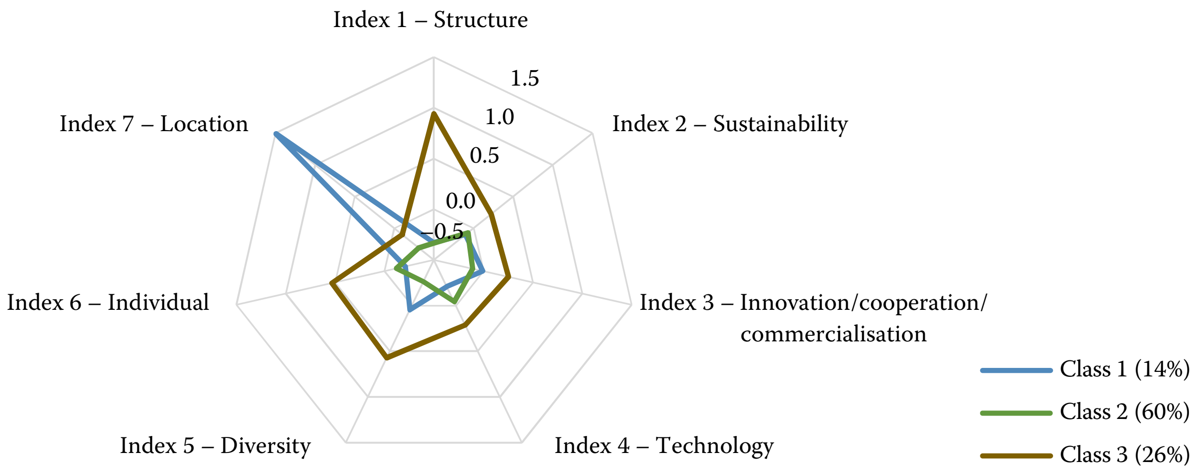

Figure 1. Indices for Czech crop farms
*(%) of farms sample
Source: Authors' calculations based on the FADN CZ 2005–2017 data (FADN CZ Database 2018)

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Table 4. Descriptive statistics by class, Czech crop farms – z-scores

Deviations from sample means*	Class 1 (n = 626)	Class 2 (n = 2 644)	Class 3 (n = 1 159)
Index 1 – Structure			
Family/hired labour ratio	0.1208	0.1944	–0.5088
Land (ha)	–0.3755	–0.4144	1.1483
Form ownership: (1: self-employment, 2: legal person, 3: cooperative form)	–0.4990	–0.5088	1.4303
Index 2 – Sustainability			
Chemicals use (per ha)	–0.5051	0.0011	0.2704
Organic (probability)	0.0318	–0.0699	0.1424
Environmental subsidies (per ha)	0.0791	–0.1128	0.2145
Index 3 – Innovation/cooperation/commercialisation			
Net investment	–0.0912	–0.1258	0.3361
Net investment ratio (per total assets)	0.1049	–0.0939	0.1575
Share land rented	–0.2728	–0.2205	0.6505
Biofuel production (probability)	–0.0733	–0.0856	0.2349
Index 4 – Technology			
Capital/labour ratio (per hour)	–0.1720	0.0524	–0.0265
Materials per ha (per ha)	–0.3346	–0.1039	0.4178
Labour per ha (hour per ha)	–0.1170	–0.0206	0.1102
Input services share	–0.2584	0.0148	0.1059
Index 5 – Diversity			
Herfindahl index (sqrt[$\Sigma(y_i/Y)2$])	–0.4290	–0.4101	1.1673
Livestock output share	0.3447	–0.1884	0.2435
Other output share	–0.1682	–0.2052	0.5590
Livestock production (probability)	0.4489	–0.1569	0.1155
Other output (probability)	–0.1474	–0.3625	0.9066
Index 6 – Individual			
Age (years)	–0.0667	–0.0214	0.3757
Education (1: primary, 2: secondary, 3: high)	–0.3508	–0.2197	0.6908
Index 7 – Location			
LFA subsidies (per ha)	0.9880	–0.2013	–0.0744
Altitude (1: < 300m, 2: 300–600m, 3: > 600m)	1.2058	–0.2564	–0.0665
Less favoured area (1: not to 3 severely disadvantaged)	2.1588	–0.4467	–0.1470

*Deviations from sample means (= 0), z-scores based, scaled values; n – observations
Source: Authors' calculations based on the FADN CZ 2005–2017 data (FADN CZ Database 2018)

outside LFA and at lower altitudes. The share of unpaid labour is negligible. Farms dispose with above-average capital facilities and share of external input services. The production of biofuels is likely to occur together with other production.

In the second stage separate SFA-TRE models were carried out for each class [Table 5; Table S3 and Supplementary Material S1 in electronic supplementary material (ESM); for ESM see the electronic version]. Technical efficiency was calculated by two methods. The first one was based on the LCM for three different groups of farms (TE LCM). The second TE indicator was calculated for the whole dataset and then for each class of farms an average level of TE (common frontier) was calculated. This TE was calculated for comparative purposes to relate the TE of the different classes.

Input variables were normalised so the obtained parameters can be considered as output elastici-

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Table 5. Czech crop farms – production function estimates true random effects panel translog model per class; 2005–2017

	Class 1	Class 2	Class 3	All
First-order parameters				
x_1	0.349***	0.240***	0.080**	0.257***
x_2	0.095*	0.112***	0.058**	0.097***
x_3	0.065*	0.062***	0.137***	0.090***
x_4	0.258***	0.441***	0.459***	0.428***
x_5	0.254***	0.195***	0.231***	0.122***
t	0.038***	0.036***	0.023***	0.033***
Second-order parameters				
x_1 sq	0.082	0.328***	0.534***	0.256***
x_2 sq	–0.075	0.081	0.019	–0.004
x_3 sq	0.027	–0.015	0.035	–0.009
x_4 sq	0.337	0.136**	–0.260***	0.066
x_5 sq	0.036***	0.026***	0.037***	0.017***
t_2	–0.018***	–0.013***	–0.013***	–0.016***
x_{1-12}	0.164	–0.178***	–0.221***	–0.163***
x_{1-3}	–0.090	–0.020	0.045	0.016
x_{1-4}	–0.278	–0.069	–0.090	–0.081*
x_{1-5}	0.002	–0.118**	–0.187***	–0.056*
x_{2-3}	–0.022	0.060	0.017	0.054**
x_{2-4}	–0.046	0.012	0.131***	0.056
x_{2-5}	–0.020	0.014	0.008	0.002
x_{3-4}	0.096	–0.087**	–0.030	–0.060*
x_{3-5}	0.015	0.110***	–0.049	0.022
x_{4-5}	–0.014	–0.017	0.161**	0.024*
x_{1t}	0.037***	0.013***	0.025***	0.017***
x_{2t}	0.001	0.003	0.016***	0.005*
x_{3t}	0.007	–0.001	–0.013***	–0.003
x_{4t}	–0.042***	–0.004	–0.009*	–0.018***
x_{5t}	0.001	–0.007*	–0.014**	0.001
Constant	0.300***	0.216***	0.281***	0.301***
Other parameters – Usigma				
Altitude	0.887*	0.053	0.675***	0.430***
LFA	0.691	–	0.074	–0.109
FormOfOwnership	0.542	0.095	0.511**	0.316**
dInvstSubs	–0.724**	0.318	0.007	–0.110
dAEOsubs	0.404	0.335**	–	0.451***
dLFAsubs	0.030	–0.250	–	–0.023
dES	–0.620	–1.229***	–	–0.779***
gUAA	–0.008	0.117	–	1.092***
gAEOha	0.609	–	0.345***	–
gLUha	–0.306	–0.232	–	–
gLFAha	–0.741	–	1.137**	–
gIO	1.980***	2.015***	–	–
dAge	–	–	–	–0.141*

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Table 5 to be continued

	Class 1	Class 2	Class 3	All
dChemie	–	–	–1.001	0.036
gES	–	–	–	–1.354***
Lambda	0.920	0.801	1.552	1.090
Observations	626	2 644	1 159	4 429
Number of farms	111	344	145	506
TE (LCM)	0.859	0.876	0.836	0.863
TE (common frontier)	0.798	0.836	0.856	0.836
Returns to scale	1.021	1.050	0.965	0.994

Significance at *** $P < 0.01$, **$P < 0.05$, *$P < 0.1$; x_1 – Land; x_2 – Labour; x_3 – Capital; x_4 – Materials; x_5 – Chemicals; sq – squared; t – time variable expressing technical change; t_2 – dynamics of change over time; *Altitude* – < 300m, 300–600m, > 600m; *LFA* – less favoured area (1, ..., 3); *FormOfOwnership* – form ownership category (1: self-employment, 2: legal person, 3: cooperative form); *dInvstSubs* – investment subsidies (0/1); *dAEOsubs* – agro-environmental subsidies (0/1); *dLFAsubs* – LFA subsidies (0/1); *dChemie* – crop protection dummy (0/1); *dfh_labor* – unpaid labour (0/1); *dES* – economic size (1, ..., 4); *gUAA* – utilised agricultural area group (1, ..., 4); *gAEOha* – environmental subsidies per ha group (1, ..., 4); *gLFAha* – LFA subsidies per ha group (1, ..., 4); *gIO* – material costs crop production ratio group (1, ..., 4); *dAge* – age group (1, ..., 4); *TE* – technical efficiency; LCM – latent class model

Source: Authors' calculations based on the FADN CZ 2005–2017 data (FADN CZ Database 2018)

ties evaluated at the geometric mean of the sample. The signs of the elasticity of Land, Labour, Capital, Materials and Chemicals met expectations, i.e. x_1, x_2, x_3, x_4, x_5 variables are positive (Table 5). Farms included in Class 3 have a greater area of agricultural land and produce significantly more than farms of Class 1 and Class 2 (Table 4). At the same time, based on common frontier, they have the highest level of TE (0.856), quite high level of TE change (2.89), and show the highest performance (measured by productivity in EUR per year). Technical efficiency change significantly varies between classes. Classes 1 and 3 showed similar values (2.46 and 2.89, respectively; Figure 2). Farms in Class 1 have the lowest level of TE based on common frontier (0.798). Farms of Class 1 and Class 2 have increasing return to scale (1.021 and 1.050, respectively) as opposed to decreasing returns to scale (0.965) of Class 3 farms (Table 5).

Class 1. All production elasticities are positive; the highest elasticity is displayed by production factor Land (0.349); Capital, in contrast, has a low impact on firms' output (0.065). TCH has positive

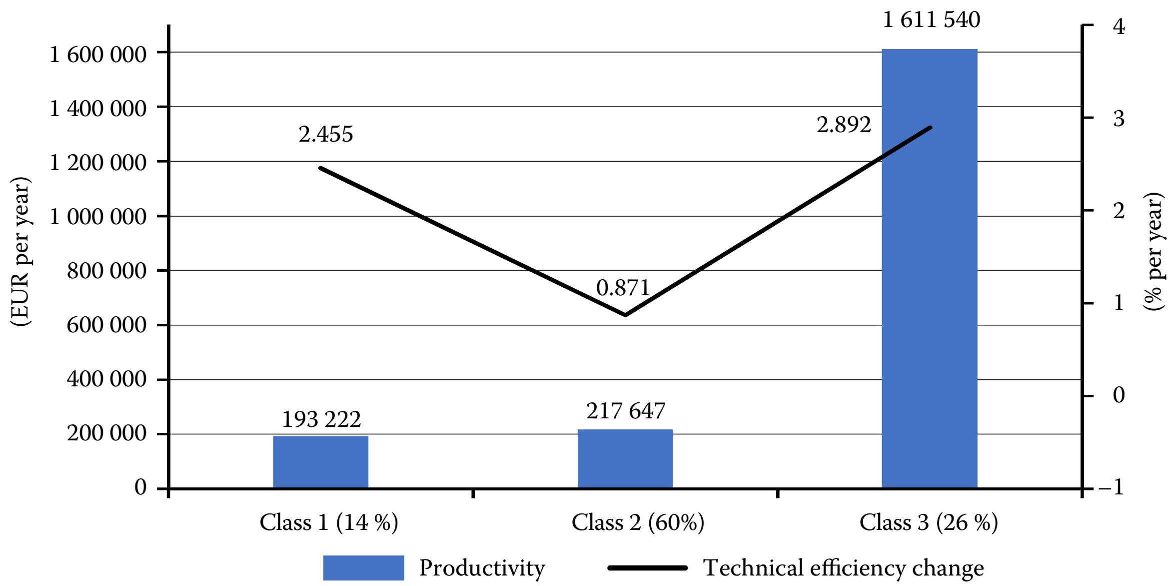

Figure 2. Productivity, technical efficiency change; 2005–2017

Source: Authors' calculations based on the FADN CZ 2005–2017 data (FADN CZ Database 2018)

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impact on production. It is characterised by material-saving, and Land-, Capital-, Labour- and Chemicals-intensive behaviour [Table S3 and Supplementary Material S1 in electronic supplementary material (ESM); for ESM see the electronic version]. Farm altitude positively contributes to the variance of technical inefficiency (TI). Farms that are recipients of subsidies on investments have lower variance of TI. The higher share of material input on total crop production increases TI variance.

Class 2. The highest elasticity belongs to the production factor Material (0.441). The other factors have lower impact on production output (0.112 for Labour and 0.062 for Capital). Among the factors that were incorporated to the variance of the TI component, there are several that have a significant impact on it. AEO subsidies increase the TI variance, whereas the ES category, in contrast, decreases. The higher share of material input on total crop production decreases the TI variance.

Class 3. Elasticity of the production factor Labour is the lowest of all production factors (0.058). Material has the highest impact on production with the value of 0.459. The sector is characterised by positive and significant impact of TCH, where Capital, Material, and Chemicals are of saving, and Land- and Labour-are of Intensive-using behaviour [Table S3 and Supplementary Material S1 in electronic supplementary material (ESM); for ESM see the electronic version]. Farm attitude, form of ownership, AEO and LFA subsidies increase variance of the TI component.

All classes. Farm altitude, form of ownership and AEO subsidies variable increase the variance of TI. ES of the farm and the farmers age contribute to decreasing the TI variance.

A positive relation between farm size and efficiency was accordingly described by Bojnec and Latruffe (2013). On the other hand, farmers have to bear in mind the results of Baráth and Fertő (2015) that there is no room to improve productivity by increasing farm size unless farms switch technologies. Consequently, agricultural policies for increasing productivity should concentrate on technological progress.

CONCLUSION

Results for farms with crop production in the Czech Republic for the period 2005–2017 indicate the existence of three latent significantly heterogeneous classes of farms. Farms in these three classes differ significantly over time with regard to economic performance and technical development. The main conclusions are as follows: innovative crop farms are likely to produce more. Family farms as well as smaller farms, at least in terms of acreage, are not necessarily more sustainable. Highly sustainable crop farms are likely to be at lower altitudes and are not situated in LFAs.

Capital intensity and low labour utilisation correlate positively with economic size. However, the productivity of farms is not unrelated to the ES, share of unpaid labour, or form of ownership.

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