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Heterogeneity and efficiency of food processing companies in the Czech Republic

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Abstract: In the paper, the observed heterogeneity and technical efficiency of Czech food processing companies are investigated. Recent studies proved that food processing firms' heterogeneity can influence the result of the efficiency estimation. For the empirical study, the panel data set from the years 2005–2012 containing 2854 observations of 607 food processing companies was used. Variables representing heterogeneity factors were incorporated in the mean of inefficiency term distribution of the Battese and Coelli model (1995). The models were estimated in the form of translogarithmic production function using the Stochastic Frontier Approach. The results indicate the presence of significant heterogeneity among the firms in the analysed branches and among different branches of the food processing industry.

Keywords: inefficiency effects model, marginal effects, production function, Stochastic Frontier Analysis

The number of researches concerning different methods of efficiency measuring has increased rapidly during the last decade. There are two main methods to model frontier efficiency, namely the Data Envelopment Analysis (DEA) and the Stochastic Frontier Analysis (SFA). This paper deals with modelling the firm specific heterogeneity using the SFA.

For capturing heterogeneity, the traditional models of SFA have been extended. Initially, when the heterogeneity accounting studies started to develop, it was assumed that the time-invariant part in the model represents inefficiency, and the time-varying part can be seen as the firm or unit specific heterogeneity. The time-invariant technical inefficiency models assume that technical efficiency does not change over time. This might be the case in the situations where, for example, inefficiency is associated with the managerial ability, or if the time period of the panel is relatively short. In the time-varying models, inefficiency is represented as a part changing over time, that appears as more realistic. However, in the recent papers, the pert not changing in the time is mainly assumed as the firm specific heterogeneity, while the time variant part is considered as inefficiency (Greene 2011) Which one of these interpretations is correct is not a simple question. It is obvious that there are the firm specific heterogeneity factors which do not change in time and which are beyond the managerial control. These should of course be interpreted as the time invariant heterogeneity (Kopsakangas-Savolainen and Svento 2008).

Both approaches (DEA and SFA) assume that firms are not heterogeneous but inefficient, since all inefficiency scores are estimated by assuming a homogeneous technology available to all producers. This suggests that the impact of inefficiency in agriculture is often overestimated (Hockmann and Pieniadz 2008).

Significant studies on the measured and unmeasured heterogeneity were carried out by Greene (2003, 2005a). Greene (2003) shows and compares models with the measured (Truncated Normal model) and unmeasured (Random Parameters model) heterogeneity using panel data set on health care delivery. Furthermore, Greene proposed several model specifications that are able to take into account the unmeasured heterogeneity. In 2002 Greene proposed the "True" Fixed Effect model and "True" Random Effects model; in 2005 Greene investigated the unmeasured heterogeneity using the Random Parameters and Latent Class models. Alvarez et al. (2003, 2004) originated the Random Parameters model with a fixed unobserved effect which associates with the management.

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Among the studies focused on the measured heterogeneity there are, for instance, Gorton and Davidova (2004), Bojnec and Latruffe (2013), who analysed the technical efficiency (TE) and the relationship between the size and farm efficiency in the CEECs. Gorton and Davidova observed no clear relationship between the size and the TE; whereas Bojnec and Latruffe found that the farm size positively affected the TE in Slovenia and in the Czech Republic, while the relationship was ambiguous in Poland. Latruffe et al. (2004) analysed the TE and its determinants for farms in Poland specializing in crops and livestock, and found two important determinants of the TE: the farmers' education and the market integration of the farm. Špička (2015) compared the technical efficiency of Czech, Polish and Slovak milk processing companies, which were divided into two equal-size groups according to the value of the mean Malmquist index, and concluded that Czech and Slovak milk processors had a lower efficiency improvement than Polish companies.

Hockmann and Pieniadz (2008) applied the Fixed Management model derived by Alvarez et al. (2003) to examine the farms' heterogeneity of Polish agriculture. Their results revealed the existence of the unobserved factor that captures the effect of environmental conditions, differences in the factors such as the climate condition, soil fertility and human capital, including the management skills. (Barátha and Fertő 2015). Furthermore, their results confirmed that the standard SFA models overestimate the TE. Čechura (2010) estimated the TE of Czech agriculture using different SFA models and proved that only those model specifications that allowed for the capture of the time-invariant firm heterogeneity provided consistent estimates of the TE.

Barátha and Fertő (2015) estimated the Latent Class model for Hungarian crop farms to capture the heterogeneous technology, and concluded that it is especially important to account for technological differences when examining the TE. Brasili et al. (2007) estimated the TE of meat processing companies in Hungary and Emilia-Romagna and proved significant difference among firms of two analysed geographic regions. The sources of the food processing industry productivity growth in the Czech Republic were investigated by Čechura and Hockmann (2010) based on the production function estimation and the calculation of the TFP index for Czech food processing companies. The technical efficiency analysis in view of the heterogeneity of the food processing industry in the Czech Republic was conducted by Čechura and Hockmann (2011, 2014). In these researches, the authors dealt with the unobserved heterogeneity using the Random Parameters model. In the first paper, the authors compare different model specifications and concluded that the more flexible form – the Random Parameters model with sector effects and heteroscedasticity – is the best specification for the Czech food processing industry representation (Čechura and Hockmann 2011). The authors concluded that the intersectoral heterogeneity and heterogeneity among firms are the important characteristics of the Czech and the EU food processing industry. Kroupová (2010), Malá (2011) analysed the technical efficiency of organic farms in the Czech Republic using the Pitt and Lee Random effects model with heteroscedasticity and heterogeneity, and found out that there exists a significant difference in the TE between the conventional and organic farms in Czech agriculture. Rudinskaya (2015) investigated the unobserved heterogeneity of Czech meat processing farms using a different model of the SFA, and proved a considerable impact of the firms' heterogeneity on the TE estimation. Despite the existing number of studies focused on heterogeneity of Czech food processing companies, there is a lack of researches dealing with the observed heterogeneity, i.e. researches that could explain which factors affect difference in TE at the intrasectoral and intersectoral level.

In this paper, the productivity of the Czech food processing industry was analysed. The aim is to conduct a comparative analysis among companies inside different branches of the food processing industry and among the different branches, and to identify the productive and less productive companies in the Czech food processing. In addition, the impact of heterogeneity factors on the technical efficiency using the Battese and Coelli model (1995) is analysed. In this model, different heterogeneity factors (sources of inefficiency) are incorporated into the mean of the truncated normal distribution of the inefficiency term. The model allows analysing firm-specific factors on the technical efficiency (technical inefficiency). The Battese and Coelli model is used to study the observed intra- and intersectoral heterogeneity of Czech food processing companies.

The research questions to be addressed are:

(1) Does indebtedness significantly affect the TE of food processing companies?

(2) Does the relationship between the firm's size and the TE of food processing companies exist?

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(3) Is there a significant difference between the sectors of the food processing industry (i.e. intersectoral heterogeneity)?

MATERIALS AND METHODS

Stochastic Frontier Analysis (SFA)

Following Farrell (1957), many different methods have been considered for the estimation of efficiency. Two widely used approaches are the Data Envelopment Analysis (DEA), which is non-parametric and deterministic, and the Stochastic Frontier Analysis (SFA), which is, on the contrary, parametric and stochastic.

To study the determinants of technical efficiency we used the SFA methodology developed by Aigner et al. (1977). The SFA method is based on an econometric (i.e., parametric) specification of a production frontier. Using a generalized production function and panel data, this method can be depicted as follows:

$$y_i = f(x_{ijt};\beta) \times exp(\varepsilon_{it}) \quad (1)$$

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

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

The second component, u_{it}, captures the technical inefficiency relative to the stochastic frontier. The inefficiency term u_{it} is non-negative and it is assumed to follow the half-normal, truncated-normal, gamma or exponential distribution (Kumbhakar and Lovell 2000).

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

$$TE_{it} = \frac{y_{it}}{y_{it}^*} = \frac{f(x_{ijt};\beta) \times exp(v_{it} - u_{it})}{f(x_{ijt};\beta) \times exp(v_{it})} = exp(-u_{it}) \quad (2)$$

Because $y \leq y^*$, the TE index is bounded between 0 and 1; the 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 the firm-level TE can be calculated from the error term ε_i as the expected value of $-u_i$ conditional on ε_i, which is given by

$$E[u_i|\varepsilon_i] = \frac{\sigma_* \phi\left(\frac{\mu_{*i}}{\sigma_*}\right)}{\Phi\left(\frac{\mu_{*i}}{\sigma_*}\right)} + \mu_{*i} \quad (3)$$

where $\phi(\cdot)$ present the standard normal density and $\Phi(\cdot)$ the standard normal cumulative density functions;

$\mu_{*i} = \frac{-\sigma_u^2\epsilon_i}{\sigma_v^2+\sigma_u^2}$ and $\sigma_*^2 = \frac{\sigma_v^2\sigma_u^2}{\sigma_v^2+\sigma_u^2}$ for the half normal distribution of inefficiency term

$\mu_{*i} = \frac{\sigma_v^2\mu-\sigma_u^2\epsilon_i}{\sigma_v^2+\sigma_u^2}$ and $\sigma_*^2 = \frac{\sigma_v^2\sigma_u^2}{\sigma_v^2+\sigma_u^2}$ for the truncated-normal distribution of inefficiency term

Thus, the TE measure for each farm is equal to

$$TE_i = exp(-E[u_i|\varepsilon_i]) \quad (4)$$

SFA and heterogeneity

It is possible to take heterogeneity into account by including those effects in the mean and/or variance of the distribution of inefficiency (observed heterogeneity) or by randomizing some parameters of the stochastic frontier model (unobserved heterogeneity).

Unobserved heterogeneity. During the past two decades, there was a development of various forms of econometric methods, which can, especially on the panel data, identify the unobserved heterogeneity.

Unobserved heterogeneity can be taken into account by randomising some of the parameters of the model; in this case, it is assumed that the randomisation captures all time invariant unobserved heterogeneity.

There are models able to introduce the unobserved heterogeneity: the True Fixed and the Random Effects Model (Greene 2005b), the Random Parameters Model (Greene 2005a), the Fixed-Management Model (Alvarez et al. 2006).

Observed heterogeneity. Observed heterogeneity can be introduced into the specification by several methods. A common approach deals with incorporating of a vector of variables z_i, which contains the information about heterogeneity, directly into the model. In this case, z_i appears to be a goal function itself.

$$y_i = \beta' x_i + \alpha' z_i + v_i - u_i \quad (5)$$

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Two other methods of introducing the observed heterogeneity into the frontier model allow capturing heterogeneity in the variance parameter and in the mean of the technical inefficiency term.

This paper deals with the observed heterogeneity that can be explained by different exogenous variables. Our approach assumes that exogenous factors affect the technical efficiency and are modelled in the technical inefficiency term. The model for empirical study is based on Battese a Coelli (1995). It is supposed that the inefficiency terms non-negative random variables capturing the firm-specific and time-specific deviations from the frontier, associated with the technical inefficiency. In equation (5) is specified as

$$u_{it} = z_{it}\delta + w_{it} \tag{6}$$

where z_{it} is a vector of the firm-specific time-variant variables (exogenous factors or variables explaining inefficiency) exogenous to the production process, and δ is an unknown vector of J parameters to be estimated. The error term $w_{it}\ N(0, \sigma_w^2)$ is truncated from below by the variable truncation point $-z_{it}\delta$. The stochastic frontier inefficiency effects model allows for the estimation of the impact of different factors on the technical inefficiency.

Therefore, the technical efficiency corresponding to the production frontier and inefficiency effects is defined as

$$TE_{it} = exp(-u_{it}) = exp\{-z_{it}\delta - w_{it}\} \tag{7}$$

For the estimation, the production function in the Translogarithmic (transcendental logarithmic) form was used.

The production function in the translogarithmic form with three production factors and a proxy time variable is represented as follows:

$$\begin{aligned}\ln(Y) = {} & \ln(A) + \alpha_K\ln(K) + \alpha_L\ln L + \alpha_M\ln M + \alpha_T T + \\ & 0.5\beta_{KK}\ln(K)\ln(K) + 0.5\beta_{LL}\ln(L)\ln(L) + \\ & \ln(M)\ln(M) + 0.5\alpha_{TT}TT + B_{KL}\ln(K)\ln(L) + \\ & \beta_{KM}\ln(K)\ln(M) + \beta_{LM}\ln(L)\ln(M) + \alpha_{KT}\ln(K)T + \\ & \alpha_{LT}\ln(L)T + \alpha_{MT}\ln(M)T + v_{it} - u_{it}\end{aligned} \tag{8}$$

where A is the total factor productivity, L is the labour variable, K is the capital variable, M is the material variable, Y is the output variable, T is the time trend variable representing the technical change.

Marginal effects calculation

The marginal effect of each exogenous variable (z_{pit}) on the technical efficiency can be calculated from (Kumbhakar a Lovell 2000):

$$\partial TE_{it}/\partial z_{pit} = \frac{\partial E[\exp(-u_{it})\,|\varepsilon_{it}]}{\partial z_{pit}} = TE_{it}\Psi\delta_p, \tag{9}$$[1]

where $\Psi = \sigma_w^{-1}\left[\sigma_w + \frac{\phi(\rho)}{1-\Phi(\rho)} - \frac{\phi(\sigma_w+\rho)}{1-\Phi(\sigma_w+\rho)}\right]$ and

$\rho = \sigma_w^{-1}\left[\delta_0 + \sum_{p=1}^{J}\delta_p z_{pit}\right]$

The total differentiation (4) with respect to t gives:

$$\frac{\partial TE_{it}}{\partial t} = \frac{\partial TE_{it}}{\partial z_{1it}}\frac{\partial z_{1it}}{\partial t} + \frac{\partial TE_{it}}{\partial z_{2it}}\frac{\partial z_{2it}}{\partial t} + \dots + \frac{\partial TE_{it}}{\partial z_{Jit}}\frac{\partial z_{Jit}}{\partial t} + \\ + \frac{\partial TE_{it}}{\partial w_{it}}\frac{\partial w_{it}}{\partial t} \tag{10}$$

For the estimation of the production function, the technical efficiency and marginal effects, the software Stata 11.2 was used.

Data set

The panel data set was collected from the Albertina database. The analysis uses information from the final accounts of companies whose main activity is food processing in the period from 2005 till 2012. The database represents 9 branches of the food processing industry, but for the purposes of this study, 4 branches were chosen, that are the CA 101 – Preserved meat and meat products, CA 105 – Dairy products, CA 107 – Bakery and farinaceous products, CA 108 – Other food products (sugar, cocoa, chocolate, tea, coffee, spices, ready-mix, homogenised food preparations and dietetic food). The number of observations of other sectors was not representative for the production function estimation. Since the share of 4 chosen sectors in the total food processing industry output is more than 79% (Table 1), it is assumed, for the purpose of this paper, that these branches represent the whole industry. After the cleaning process (removing companies with missing observations and negative values of the variables), the unbalanced panel data set contains 2854 observations of 607 food processing Czech companies. The share of branches is represented in Table 1.

The following variables were used in the analysis: Output, Labour, Capital and Material. Output is

[1]Marginal effects on technical efficiency can be calculated as: $\frac{\partial TE_{it}}{\partial z_{pit}} = -TE_{it} \times \frac{\partial E(u_{it})}{\partial z_{pit}}$, because $TE_{it} = exp(-u_{it})$ (Zhu et al. 2008).

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Table 1. Significance of the main branches in the dataset (as a percent of the total industry output)

Year	Average output per firm	Number of observa-tions	Share of branch in industry output							
			CA 101	CA 103	CA 104	CA 105	CA 106	CA 107	CA 108	CA 109
2005	235 031	453	23.3	2.7	5.3	25.8	4.8	8.9	21.8	5.4
2006	258 172	501	24.2	3.0	3.7	24.2	4.4	13.6	20.2	6.3
2007	234 448	571	29.1	2.8	3.9	27.5	3.0	8.5	16.9	7.0
2008	213 914	643	26.7	2.5	4.2	24.1	3.9	8.6	22.4	6.4
2009	219 950	660	27.1	2.9	1.2	21.7	3.8	8.3	21.8	12.0
2010	241 908	666	26.1	2.8	4.0	20.2	3.5	10.0	20.6	11.6
2011	243 030	650	27.5	2.6	4.4	19.2	2.8	8.7	20.7	13.1
2012	255 807	552	26.5	2.7	4.4	18.9	3.5	9.2	20.7	14.0

CA 101 = Preserved meat and meat products, CA 103 = Processed and preserved fruit and vegetables, CA 104 = Vegetable and animal oils and fats, CA 105 = Dairy products, CA 106 = Grain mill products, starches and starch products, CA 107 = Bakery and farinaceous products, CA 108 = Other food products, CA 109 = Prepared animal feeds

Source: own processing

represented by the total sales of goods, products and services of the food processing company. In order to avoid price changes, Output was deflated by the price index of food processing companies according to the branch (2005 = 100). The Labour input is used in the form of the total personnel costs per company, divided by the average annual regional wage. The source of regional wages is the Czech Statistical Office. The Capital variable is represented by the value of tangible assets. The Material variable are the total costs of the material and energy consumption per company. Capital and Material variables were deflated by the price index of industrial sector (2005 = 100). The Output, Capital, Material variables are measured in thousand CZK. Since the Labour variable is a coefficient (see the above-mentioned Labour variable definition), there is no necessity to deflate the variable to eliminate price changes

According to the purpose of the study, 3 variables and a time variable were chosen for the companies' heterogeneity effects representation. These variables are assumed to have the impact on the firms' technical efficiency through their financial position and the scale effect captured by the size variable. Table 2 observes variables introduced as explanatory variables in the mean of distribution of the inefficiency term of Battese and Coelli model (1995).

RESULTS AND DISCUSSION

As a standard empirical application of Battese and Coelli (1995) model, the maximum likelihood method for the model estimation was used. The parameter estimates of the production function and inefficiency effects model for each branch are shown in Table 3.

Preserved meat and meat products: The first-order estimated parameters are significant at 1% level of significance under the z-test except the Capital variable. The assumption of monotonicity and quasi-concavity is fulfilled for all production factors. Since the values of the production factors were normalised by their arithmetic means after the logarithmic transformation, in the trans-logarithmic model these coefficients denote the variation or the possible percentage change in the aggregate output as a result of one percent change in the input, that is, the production elasticity. All production elasticities are positive; the highest

Table 2. Explanatory variables ($\boldsymbol{z}_i$) of the inefficiency effects model and their definitions

Variable	Definition
Long-term debt	Share of long and intermediate run loans in total assets (%)
Short-term debt	Share of short run loans in total assets (%)
Company size	Represented by dummy-variables. Variable V1 stands for companies with less than 10 employees, V2: 11–49, V3: 50–149, V4: 150 and more employees
Time trend	Time = 1 for 1995, time = 10 for 2004

Source: own processing

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Table 3. Estimated parameters of the Battese and Coelli Model (1995) (Intrasectoral heterogeneity)

			Coefficient			
			preserved meat and meat products	dairy	bakery and farinaceous products	other products
First-order parameters	Constant		0.2537***	0.1852***	0.3054***	0.3986***
	β_T		–0.0205**	–0.0539***	0.0054	–0.0118
	β_L		0.3143***	0.3174***	0.0041	0.2991***
	β_K		0.0027	0.0322**	0.0917***	0.0404***
	β_M		0.6159***	0.6616***	0.8259***	0.6348***
Second-order parameters	β_{TT}		–0.0028	–0.0050	–0.0032	–0.0055
	β_{LT}		–0.0081	–0.0395***	–0.0222**	–0.0207*
	β_{KT}		0.0049	0.0227***	0.0117***	0.0166***
	β_{MT}		0.0087	0.0200***	0.0010	0.0036
	β_{LL}		–0.3303***	0.1905***	–0.2291***	–0.2446***
	β_{KK}		–0.0841***	–0.0333	0.0493***	–0.0682***
	β_{MM}		0.2116***	0.1508***	–0.2370***	0.2146***
	β_{LK}		–0.1344***	0.0191	–0.0423***	–0.0706***
	β_{LM}		–0.1892***	–0.1562***	–0.1653***	–0.1636***
	β_{KM}		0.0227*	–0.0301**	–0.0242***	–0.0172
Parameters of heterogeneity in mean of inefficiency term	Long-term debt		0.0836	0.0001	0.0222***	–0.4045*
	Short-term debt		0.0118	0.0649**	0.0106**	0.0464*
	Company size	V2	–34.4354*	–1.2266	–45.2191***	–63.3179***
		V3	–157.8700**	–18.7382*	–79.2154***	–160.6067***
		V4	–242.5831**	–5.1523	–151.4800***	–49.7142***
	Time trend		–3.7912	–4.5708	1.0284	–5.1129***
	Constant		–58.4276*	–3.0536**	–29.9486***	–5.6936
	Lambda		72.7301***	9.7285***	42.2387***	29.2684***
	TE		0.6947	0.9176	0.7101	0.7869
	RTS		0.9319	1.0112	0.9217	0.9747

***, **, * denotes significance at the 1%, 5%, and 10% level, respectively

Source: own processing

elasticity displays the production factor Material (0.6159). The production factor Capital, in opposite, has a low impact on firms' output (0.0027). The parameter λ is the relation between the variance of u_{it} and v_{it}. Thus, the parameter indicates the significance of the technical inefficiency in the residual variation. A value larger than one suggests that the variation in u_{it} prevails the variation in the random component v_{it}. The technical change has a negative impact on production. It is characterised by the labour-saving, and capital- and material-intensive behaviour.

Dairy products: The parameters of the model are statistically significant at 1% level of significance, except Capital, that is significant at 5% level. The slopes of the coefficients are positive, that is consistent with the economic theory. The highest elasticity belongs to the production factor Material (0.6616). The other factors have a lower impact on the production output (0.3174 for Labour and 0.0322 for Capital). The estimated parameters of production factors satisfy the curvature assumption of quasi-concavity in inputs. The parameter λ is more than one which indicates the presence of inefficiency in the data. The technical change is characterised by a negative impact on production, and labour-saving, but capital- and material-intensive features.

Bakery and farinaceous: The criteria of theoretical consistency, i.e., the assumptions regarding the positive slope of the production function (monotonicity), and the curvature assumption (quasi-concavity in inputs) are fulfilled in the case of all production factors. The elasticity of the production factor Capital is the lowest among the production factors (0.0917). Material has the highest impact on production with

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the value of 0.8259. The parameter λ indicates the significance of the term in the residual variation. The sector is characterised by a positive, but insignificant impact of the technical change, where labour is of saving, and capital and material are of the intensive-using behaviour.

Other products: Monotonicity and quasi-concavity (diminishing marginal productivity) assumptions are fulfilled for all production factors. The first-order parameters are significant at 1% level of significance. The production factor Material has the highest elasticity (0.6348), whereas the elasticity of Capital is 0.0404. The significant value of parameter λ supposes that the variation in production may be explained by V term, presented in data. The parameter β_T is negative and supposes a negative impact of the technical change on production output. It is characterised by the material- and capital intensive and labour-saving behaviour.

Almost all branches except the Dairy products (CA 105) demonstrate decreasing returns to scale, that is the output increases by less than that the proportional change in inputs. The analysis determined slightly increasing, rather constant returns to scale in the case of the Dairy products (CA 105). The most technically efficient branch is the Dairy products (91.76%); a less efficient are the Preserved meat and meat products (69.47%). Table 4 represents the calculated marginal effects of variables, explaining heterogeneity, on the technical efficiency of food processing companies. Since not all variables have significant marginal effects on the TE, only those with a substantial impact are displayed in the Table 4.

The estimates of the technical inefficiency effects model (Table 3) and the estimates of the marginal effect on technical efficiency show that both the long-term and the short-term debt significantly increase the technical inefficiency at the branch of Bakery and farinaceous products (CA 107). The short-term debt has a significant negative impact on the technical efficiency at the branch of Dairy products (CA 105), whereas the impact of the long-term debt is negative, but insignificant. At the branch of the Preserved meat and meat products (CA 101), the direction of impact of both the long- and short-term debt on the TE is negative, but statistically insignificant. The short-term debt variable at the branch of Other products (CA 108) demonstrates a negative impact on the technical efficiency, while the long-term debt variable has a positive impact on the technical efficiency. This fact can be explained by the possible positive effect of investments, the source of which is the long-term debt, on the company's activity and technical efficiency.

Another variable, the firms' size, reduces the technical inefficiency. These results suggest that a higher size of a firm, represented by the number of workers, positively affects its efficiency (see Tables 3 and 4). In addition, the group of firms with more than 150 workers, i.e. the largest food processing companies, benefit from the change of their size more than other groups of companies at the CA 101 and CA 107, since the marginal effects of the dummy variable V4 is represented by the highest number (Table 4). At the sectors of Dairy products (CA 105) and Other products (CA 108), the highest positive impact on the technical efficiency has the dummy variable V3, which stands for the companies with the number of workers 50-149 (Table 4). The variable Time trend, introduced to the effects model, has a positive impact on the technical efficiency, that is, in the course of time, the technical efficiency of analysed companies increased.

Table 5 presents information about the estimated parameters of the Battese and Coelli model (1995) with introduced sectoral dummy variable for capturing intersectoral heterogeneity.

The signs of the coefficients, as well as the numerical results obtained, were found to be robust at the sample mean. The curvature condition of quasi-concavity is achieved, and it satisfies the properties of production function. The highest elasticity belongs to the production factor Material (0.6403). The other factors demonstrate a lower elasticity (0.27685 for Labour and 0.0592 for Capital). The parameter λ

Table 4. Marginal effects of exogenous variables on TE

Variable		Preserved meat and meat products	Dairy products	Bakery and farinaceous products	Other products
	V2	0.1036	0.0050	0.1677	0.3298
Company size	V3	0.4750	0.0764	0.2938	0.8366
	V4	0.7298	0.0210	0.5619	0.2590
Time trend		0.0114	0.0186	–0.0038	0.0266

Source: own processing

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Table 5. Estimated parameters Battese and Coelli Model (1995) (Intersectoral heterogeneity)

		Coefficient			Coefficient
First-order parameters	Constant	0.3279***	Second – order parameters	β_{TT}	−0.0021
	β_T	−0.0040		β_{LT}	−0.0194***
	β_L	0.2903***		β_{KT}	0.0110***
	β_K	0.0592***		β_{MT}	0.0030
	β_M	0.6403***		β_{LL}	0.1695***
Parameters of heterogeneity	*SE2*	−175.0511***		β_{KK}	−0.0673***
	SE3	−1.7129		β_{MM}	0.1441***
	SE4	−36.9069***		β_{LK}	−0.0513***
	Constant	−84.5756***		β_{LM}	−0.0917***
	Lambda	35.9725***		β_{KM}	−0.0345***
	TE	0.7019			
	RTS	0.9898			

***, **, * denotes significance at the 1%, 5%, and 10% level, respectively

Source: own processing

suggests that the important reason of differences in output among the firms is inefficiency. The technical change is characterised by the negative impact on production, and labour-saving, but capital- and material-intensive features. The returns to scale, estimated on the sample mean, demonstrate the returns to scale close to constant (0.9898). This implies that the companies of food processing industry operate at the productive scale size level. Dummy variables, which represent the intersectoral heterogeneity in the mean of the truncated-normal distribution of inefficiency term, are characterised by significance, except the variable SE3, which stands for the branch Bakery and farinaceous products (CA 107). The results indicate that the type of the food processing activity affects the mean of the inefficiency term distribution. Moreover, the technical efficiency of other sectors comparing to the Preserved meat and meat products (CA 101) is higher. These findings are consistent with the previous estimations. The differences can be explained by specific characteristics of the analysed sectors. The average technical efficiency of the food processing industry, taking into account the sectoral dummy-variables, is quite low (70.19).

CONCLUSIONS

In this paper, the technical efficiency and impact of different factors, which can be treated as heterogeneity, on technical efficiency were investigated. For the empirical analysis, the Stochastic Frontier Approach was used, the transcendental logarithmic production function was estimated using the Battese and Coelli model (1995). In this model, the variables representing heterogeneity are incorporated into the mean of the truncated-normal distribution of the inefficiency term. Additionally, marginal effects of variables, representing the intersectoral heterogeneity, were estimated. Four analysed branches – the Preserved meat and meat products, Dairy products, Bakery and farinaceous products and Other products – represent more than 79% of the total industry output.

The results show that there negative impact of the long- and short-term debt on the technical efficiency in the processing industry exists. The exception is the branch representing Other products (CA 108), where the long-term debt has a positive impact on the technical efficiency. In the case of the mentioned sector, the reason can be found in the positive impact of investments on the company's activity; the source of the former is the long-term debt. The results of the analysis display the labour-saving and capital- and material-intensive behaviour of the change of food processing companies. The short-term and long-term debt are the important sources of funding of fixed assets (Capital) and current assets (Material). At the same time, the results of production function estimation demonstrate the negative impact of indebtedness on technical efficiency of food processing companies.

The dummy variables, representing the firms' size, positively influence their technical efficiency, i.e. the technical inefficiency decreases with the growth of the company size expressed by the number of work-

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ers. The implication is, therefore, that large-scale enterprises have exhibited the potential of making noticeable improvements.

Dummy variables, representing the intersectoral heterogeneity in the mean of the truncated-normal distribution of inefficiency term, are characterised by significance, except for the variable SE3, which stands for the branch Bakery and farinaceous products. Hence, the difference in the technical efficiency between the Preserved meat and meat products, Dairy products and Other products branches of the food processing industry occurs. However, there is no statistically significant difference in technical efficiency between the Preserved meat and meat products and the Bakery and farinaceous products.

Hence, we can conclude that the heterogeneity among firms as well as among sectors is an important feature of Czech food processing, and it has to be considered when conducting a reliable analysis of the sector. This is true for the production technology and firms' conditions as well as for the technical efficiency. The latter finds its expression in the highly significant impact which the sector dummies have on the technical efficiency. Since the food processing industry is an important part of the value chain and significantly determines the competitiveness of Czech farmers, there may be proposed several policy recommendations based on the obtained results. First of all, the formulation of agrarian policy should take into account and be targeted on the processing industry. Next, since the results identified that the heterogeneity in the form of liability is a significant phenomenon in the Czech food processing industry, ways of improvement the financial situation should be found. The supports and policy tools should be sector-specific, because the food industries differ from each other. For example, the technical efficiency of the Preserved meat and meat products is much lower compared to other sectors. With respect to market position of the mentioned branch, the identified problems regarding the capital availability and the raw material procuring process should be solved. To support not only the competitiveness, the technical improvement and development of the food processing industry, but the whole agrarian sector internationally, the state programs should be of a particular interest.

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REFERENCES

Aigner D., Lovell C.A.K., Schmidt P. (1977): Formulation and estimation of stochastic frontier production function models. Journal of Econometrics, 6: 21–37.

Alvarez A., Arias C., Greene W. (2003): Fixed Management and Time Invariant Technical Efficiency in a Random Coefficient Model. Working Paper, Department of Economics, Stern School of Business, New York University.

Alvarez A., Arias C., Greene W. (2004): Accounting for Unobservables in Production Models: Management and Inefficiency. Economic Working Papers at Centro de Estudios Andaluces E2004/72, Centro de Estudios Andaluces.

Alvarez A., Amsler C., Orea L., Schmidt P. (2006): Interpreting and testing the scaling property in models where inefficiency depends on firm characteristics. Journal of productivity analysis, 25: 201–212.

Barath L., Ferto, I. (2015): Heterogeneous technology, scale of land use and technical efficiency: The case of Hungarian crop farms. Land Use Policy, 42: 141–150.

Battese G.E., Coelli T.J. (1995): A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empirical Economics, 20: 325–332.

Bojnec Š., Latruffe L. (2013): Farm size, agricultural subsidies and farm performance in Slovenia. Land Use Policy, 32: 207–217

Brasili C., Fanfani R., Maccarini E.R., Monasterolo I. (2007): A comparative analysis of the meat sector in Hungary and Emilia-Romagna: Performance and efficiency. In: 104th EAAE Seminar Agricultural Economics and Transition: What was expected, what we observed, the lessons learned. Corvinus University of Budapest, Budapest, Sept 6–8, 2007.

Cechura L. (2010): Estimation of technical efficiency in Czech agriculture with respect to firm heterogeneity. Agricultural Economics – Czech, 56: 183–191.

Čechura L., Hockmann H. (2010): Sources of economical growth in the Czech food processing. Prague Economic Papers, 2: 169–182.

Čechura L., Hockmann H. (2011): Efficiency and heterogeneity in Czech food processing industry. In: EAAE 2011 Congress Change and Uncertainty Challenges for Agriculture, Zurich, Aug 30–Sept 2, 2017.

Čechura L., Hockmann H. (2014): Heterogeneity in technology and efficiency – specifics of the food processing industry in the Visegrád countries. In: EAAE 2014 Congress Agri-Food and Rural Innovations for Healthier Societies, Ljubljana, Aug 26–29, 2014.

Farrell M.J. (1957): The measurement of productive efficiency. Journal of the Royal Statistical Society, Series A 120: 253–290.

doi: 10.17221/1/2016-AGRICECON

Gorton M., Davidova S. (2004): Farm productivity and efficiency in the CEE applicant countries: a synthesis of results. Agricultural Economics, 30: 1–16.

Greene W. (2002): Fixed and Random Effects in Stochastic Frontier Models. Working Paper 02-16, Stern School of Business, Department of Economics.

Greene W. (2003): Distinguish Between Heterogeneity and Inefficiency: Stochastic Frontier Analysis of the World Health Organization's Panel Data on National Health Care Systems. Working Papers 03-10, New York University, Leonard N. Stern School of Business, Department of Economics.

Greene W. (2005a): Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. Journal of Econometrics, 126: 269–303.

Greene W. (2005b): Fixed and Random effects in stochastic frontier models. Journal of Productivity Analysis, 23: 7–32.

Greene W. (2011): Econometric Analysis. 7th Ed. Pearson Education, Boston.

Hockmann H., Pieniadz A. (2008): Farm heterogeneity and efficiency in Polish agriculture: A stochastic frontier analysis. In: 12th EAAE Congress of the European Association of Agricultural Economists. Available at http://ageconsearch.umn.edu/bitstream/44278/2/496.pdf (accessed Dec 29, 2015).

Jondrow J., Lovell C.A.K, Materov I.S., Schmidt P. (1982): On the estimation of technical inefficiency in the stochastic frontier production function model. Journal of Econometrics, 19: 233–238.

Kopsakangas-Savolainen M., Svento R. (2008): Observed and Unobserved Heterogeneity in Stochastic Frontier Models. Working Paper No. 0805, Department of Economics, University of Oulu.

Kroupová Z. (2010): Technická efektivnost ekologického zemědělství České republiky. Ekonomická revue ERCEREI, 13: 63–75.

Kumbhakar S.C., Lovell C.A.K. (2000): Stochastic Frontier Analysis. 1st Ed. Cambridge University Press, Cambridge.

Latruffe L., Balcombe K.G., Davidova S., Zawalinska K. (2004): Determinants of technical efficiency of crop and livestock farms in Poland. Applied Economics, 36: 1255–1263.

Malá Z. (2011): Efficiency analysis of Czech organic agriculture. E+M Ekonomie a Management, 14: 14–28.

Rudinskaya T. (2015): Heterogeneity and efficiency of meat processing companies in the Czech Republic. In: 33rd International Conference Mathematical Methods in Economics MME 2015, Cheb, Sep 9–11, 2015: 713–716.

Špička J. (2015): The efficiency improvement of central European corporate milk processors in 2008–2013. Agris on-line Papers in Economics and Informatics, 7: 175–188.

Zhu X., Karagiannis, G., Lansink, A.O. (2008): Analyzing the impact of direct subsidies on the performance of the Greek Olive Farms with a non-monotonic efficiency effects model. In: 12th EAAE Congress of the European Association of Agricultural Economists. Available at http://ageconsearch.umn.edu/bitstream/43612/2/057.pdf (accessed Dec 29, 2015).

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