Estimation of technical efficiency in Czech agriculture with respect to firm heterogeneity

Odhad technické efektivnosti v českém zemědělství s ohledem na firemní heterogenitu

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Abstract: This paper deals with the estimation of technical efficiency in Czech agriculture with respect to significant firm heterogeneity. Two main questions are elaborated. The first concerns the choice of a proper model specification, distinguishing between technical inefficiency and firm heterogeneity. The second question is related to the level of technical efficiency. The results show that only those model specifications allowing for the capture of time-invariant firm heterogeneity may provide consistent estimates of technical efficiency. Specifically, the Random Parameters family of models is a superior specification for the estimation of technical efficiency in the analysis. Moreover, technical inefficiency is a significant phenomenon in Czech agriculture. The average level of technical efficiency is around 90% for agricultural companies.

Key words: firm heterogeneity, technical efficiency, SFA (Stochastic Frontier Analysis), agricultural companies

Abstrakt: Článek se zabývá odhadem technické efektivnosti v českém zemědělství s ohledem na signifikantní firemní heterogenitu. Analýza hledá odpovědi na dvě základní otázky. První otázka je spojena s výběrem vhodné modelové specifikace, která umožňuje rozlišit mezi technickou neefektivností a firemní heterogenitou. Druhá otázka se týká úrovně technické efektivnosti. Výsledky analýzy ukazují, že pouze modely, které umožňují oddělit firemní heterogenitu od technické neefektivnosti, poskytují konsistentní odhad technické efektivnosti. V analýze je superiorní specifikací pro odhad technické efektivnosti rodina Random Parameters modelů. Výsledky dále ukazují, že technická neefektivnost je signifikantním fenoménem v českém zemědělství. Průměrná úroveň technické efektivnosti se pro zemědělské podniky pohybuje na úrovni 90 %.

Klíčová slova: firemní heterogenita, technická efektivnost, SFA (Stochastic Frontier Analysis), zemědělské podniky

The extent to which the farmer is technically efficient is an important indicator of her/his competitiveness, even if it is only one component of her/his economic efficiency. Moreover, on the aggregate level, the extent to which farmers can efficiently employ their inputs tells us an important story about agriculture as a whole and its future prospects. The inefficient use of inputs decreases the competitiveness of Czech farmers internationally. Thus, reducing the waste of resources due to inefficient input use is a basic determining factor in the success or failure of Czech agriculture on the EU market.

In this paper we deal with the estimation of technical efficiency in Czech agriculture. In particular, we focus on distinguishing between technical inefficiency and firm heterogeneity. Several model specifications in the parametric approach SFA (Stochastic Frontier Analysis), which is used in this paper to estimate the production frontier and to measure technical efficiency, do not allow for a distinction to be made between technical inefficiency and heterogeneity. Thus, technical inefficiency might be overestimated, and conclusions that are based on these models might be biased.

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Two main questions will be elaborated upon in this paper. Since the differences among Czech farmers could be significant in terms of firm heterogeneity, we will examine the proper model specification for distinguishing between technical inefficiency and firm heterogeneity. The second question concerns the level of technical efficiency. Since the Czech agricultural sector experienced a couple of important institutional and economic changes in recent decades, it is timely to ask how well inputs are used.

Technical efficiency in Czech agriculture has been analyzed by several authors. Methijs et al. (1999a, 1999b and 2001) and Medonos (2006) used the non-parametric method DEA (Data Envelopment Analysis) to estimate technical efficiency in Czech agriculture. SFA was employed in studies by Curtiss (2002) and Jelínek (2006). In all the studies, technical efficiency was considered a significant phenomenon in Czech agriculture; however, the level of technical efficiency in these studies was determined by the method or model used, or was specific to the analysed data set. In light of these facts as well as further developments in estimation techniques, the analysis of technical efficiency in Czech agriculture calls for reconsideration (for the first contribution see Čechura 2009). Broader analysis of the economic performance of Czech farmers can be found in Střeleček et al. (2007), Froněk et al. (2007), Střeleček et al. (2008), etc.

THEORETICAL CONSIDERATIONS

The foundations of Stochastic Frontier Analysis (SFA) were laid independently of each other in papers by Aigner et al. (1977) and by Meeusen and van den Broeck (1977). Since then, the development of the method has occurred in several aspects: distribution of the asymmetric component, u (inefficiency); conditional estimation of inefficiency; panel data estimation (fixed effects, random effects, time variant inefficiency); risk; heterogeneity; and heteroscedasticity. The development of the method went hand in hand with advances in econometrics (see, e.g., Bayesian estimation, method for panel data, estimations based on simulation techniques /e.g. simulated maximum likelihood/ etc.).

Extensive research relating to the distinctions between firm heterogeneity and technical inefficiency was carried out in the last decade. Due to the fact that significant heterogeneity which is not taken into account in the measurement of technical inefficiency leads to a biased estimation of it, several models were developed which allow firm heterogeneity to be filtered out (to a certain degree) from the asymmetric component (inefficiency) of the model. Battese and Coelli (1995) suggested a model with a truncated distribution of inefficiency term, u, whose mean is given by $z_{it}\delta$, where z_{it} is a vector of explanatory variables associated with the technical inefficiency of the production of firm over time, and δ is a vector of unknown coefficients. Thus, Battese and Coelli introduced a model with measured firm heterogeneity. An analysis of measured and unmeasured heterogeneity was carried out by Green (2003 and 2005). Green (2003) shows and compares models with measured and unmeasured heterogeneity and discusses restrictions of employed specifications. Furthermore, Green (2002, 2003 and 2005) introduces specifications that capture the heterogeneity in the form of unmeasured heterogeneity. Green (2002) brought in the "True" Fixed Effect model and "True" Random Effects model, and in working paper (2003) and paper (2005), the Random Parameters model and Latent Class models. Random Parameters models were also studied by e.g. Tsionas (2002) and Latent Class models by e.g. Orea and Kumbhakar (2004). Álvarez et al. (2003, 2004) derive the Random Parameters model with a fixed unobserved effect (variable) which associates with management. The class of Random Parameter models and Latent Class models can be regarded as the most flexible specifications for the estimation of technical efficiency.

ESTIMATION STRATEGY AND DATA

The estimation strategy in empirical part is based on Green (2003). In comparison with Green (2003), the empirical part on one hand does not contain all fitted models by Green (see Fixed Effects model and Random Effects model with measured heterogeneity in the production function) but on the other hand does contain the "True" Random Effects model and Fixed Management model (Álvarez et al., 2004). The interpretation and comments differ as well. The examination of production models is added to the comparison of estimated technical inefficiencies. Moreover, some other model comparisons are appended. Green (2003) uses the Fixed Effects model as a benchmark. We use the Random Effects model as a benchmark, since the Fixed Effects model does not measure absolute technical inefficiency, but rather the inefficiency of one firm relative to the other firm in the sample. Subsequently, the estimated models are compared to each other and important conclusions concerning their flexibility are drawn.

The models are introduced in the following order. We begin with model which does not allow for distinguishing between firm heterogeneity and technical efficiency. The most flexible model or most general model specifications, in which all time-invariant effects are removed from the distribution of u_{it}, are commented on at the end.

In the analysis it is assumed that production possibilities can be approximated by a frontier production function. In the following applications, the deterministic part of the frontier function is modelled in the form of a translog function, i.e.:

$$\ln f(t,\, \mathbf{x}_{it}\, ;\boldsymbol{\beta}) = \alpha_0 + \sum_{j=1}^{K} \beta_j \ln x_{ijt} + \frac{1}{2}\sum_{j=1}^{K}\sum_{k=1}^{K} \beta_{jk} \ln x_{ijt} \ln x_{ikt}$$

$$\beta_t t + \frac{1}{2}\beta_{tt} t^2 + \sum_{j=1}^{K} \beta_{jt} \ln x_{ijt} t \qquad (1)$$

where $\boldsymbol{x}_{it}$ is a vector of inputs containing production factors – Labour (A_{it}), Land (L_{it}), Capital (K_{it}) and Material (M_{it}). Indexes i, where $i = 1, 2,..., N$, and t, where $t \in \Im(i)$, refer to a certain agricultural company and time, respectively, and $\Im(i)$ represents a subset of years T_i from the whole set of years T (1, 2,...T), for which the observations of *i-th* agricultural company are in the data set (see unbalanced panel). α_0 is an intercept (productivity parameter); however, in some model specifications the intercept is modified, e.g. the "True" Fixed Effects model contains α_i, which is a firm-specific (exogenous) level of productivity; (see Table 1 or for a detailed definition of stochastic frontier production models used, see Green /2002, 2003 and 2005/ and Álvarez /2003 and 2004/, for example).

REM, Truncated BC model and "True" REM are estimated by maximum likelihood (ML) method and "True" REM and RPM by maximum simulated likelihood.

Moreover, Álvarez et al. (2003 a 2004) specified Fixed Management model as a special case of Random Parameters model in the following form:

$$\ln TE_{it} = \ln f\left(x_{it}, t, m_i\right) - \ln f\left(x_{it}, t, m_i^*\right) \leq 0 \qquad (2)$$

and

$$\ln y_{it} = \ln y_{it}^* - u_{it} = \ln f\left(\mathbf{x}_{it}, t, m_i^*\right) - u_{it} = \alpha_0 + \beta_m m_i^* +$$
$$+ \frac{1}{2}\beta_{mm} m_i^{*2} + \left(\beta_t + \beta_{tm} m_i^*\right)t + \frac{1}{2}\beta_{tt} t^2 +$$
$$+ \left(\beta_x + \beta_{xt} t + \beta_{xm} m_i^*\right)' \ln \mathbf{x}_{it} +$$
$$+ \frac{1}{2} \ln \mathbf{x}_{it}' \mathbf{B}_{\mathbf{xx}} \ln \mathbf{x}_{it} + v_{it} - u_{it} \qquad (3)$$

where $m_i^* \sim \bullet(0,1)$ represents unobservable fixed management. The symbol $\bullet$ expresses that m_i^* might possess any distribution with zero mean and unit variance (see Hockmann and Pieniadz, 2008). The difference between the real (m_i) and optimal (m_i^*) management determines the level of technical efficiency (see relation 2). The model is estimated by maximum simulated likelihood.

As far as the random error (statistical noise) v_{it} and technical inefficiency term $u_{i(t)}$ of the stochastic frontier production function model are concerned, we assume that $v_{it} \sim iid\ N(0, \sigma_v^2)$, $u_{i(t)} \sim iid\ N^+(0, \sigma_u^2)$ and $u_{i(t)}$ and v_{it} are distributed independently of each other, and of the regressors (for further references see Kumbhakar and Lovell 2000). Truncated BC model has a truncated distribution of inefficiency term with mean $z_{it}\delta$.

Table 1. Fitted specifications

REM	$y_{it} = \alpha + \mathbf{x}'_{it}\boldsymbol{\beta} + v_{it} - u_i$	Pitt and Lee (1981)
Truncated BC model	$y_{it} = \mathbf{x}'_{it}\beta + v_{it} - u_{it}$ with $u_{it} = \eta_t u_i = \{\exp[-\eta(t-T]\}u_i$ and $u_{it} = z_{it}\delta + w_{it}$	Battese and Coelli (1992)
"True" FEM	$y_{it} = \alpha_i + \mathbf{x_{it}}'\boldsymbol{\beta} + v_{it} - u_{it}$	Green (2002, 2003)
"True" REM	$y_{it} = \left(\alpha + w_i\right) + \mathbf{x_{it}}'\boldsymbol{\beta} + v_{it} - u_{it}$	Green (2002, 2003)
RPM	$y_{it} = \alpha_i + \mathbf{x_{it}}'\boldsymbol{\beta} + v_{it} - u_{it}$ where $\begin{pmatrix}\alpha_i \\ \boldsymbol{\beta}_i\end{pmatrix} = \begin{pmatrix}\alpha \\ \boldsymbol{\beta}\end{pmatrix} + \begin{pmatrix}\boldsymbol{\Delta}_\alpha \\ \boldsymbol{\Delta}_{\boldsymbol{\beta}}\end{pmatrix}\mathbf{h}_i + \begin{pmatrix}\omega_{i\alpha} \\ \boldsymbol{\omega}_{i\boldsymbol{\beta}}\end{pmatrix}$	Green (2003)

In the frontier production models all variables are divided by their geometric mean. That is, fitted coefficients represent the production elasticities evaluated on the geometric mean of a particular variable.

Data set

The panel data set we use in the analysis is drawn from the database of the Creditinfo Firms' Monitor, collected by Creditinfo Czech Republic, s.r.o. The database contains all registered companies and organisations in the Czech Republic. The database involves information about final accounts, financial analyses, debtors, etc. As far as final accounts are concerned, it contains over 340 000 final accounts from 1992 to 2008.

Since the Creditinfo database does not contain information about the quantity of land employed in the production of a particular agricultural company, the database LPIS is also used. The LPIS database contains information since the year 2004. For this reason, we could not use a longer panel data set in our analysis, even though the Creditinfo database covers a longer time period. Price indexes and regional wages are drawn from the Czech statistical office. The source of official land prices is a study by Němec et al. (2006).

In our analysis, we use information from the final accounts of companies whose main activity is agriculture, according to the OKEČ classification (OKEČ 01). Therefore, the analysis concerns agricultural companies, i.e., corporations. Since not all information can be found for all agricultural companies in the database, for the analysis we use only those companies having two or more final accounts in the database over the period 2004–2007, and non-zero and positive values for the variable of interest. From the generated sample we also removed outliers. After the cleaning process, we were constrained to using the unbalanced panel data set containing 1 004 agricultural companies with 3 103 observations, covering the period from 2004 to 2007, i.e., 3.09 observations per company on average.

The following variables, as defined above, are used in the analysis: output, labour, land, capital and material. Output is represented by the total sales of goods, products and services of the agricultural company. Output was deflated by the index of agricultural prices (2005 = 100). Labour input is total personnel costs per company, divided by the average annual regional wage in agriculture (region = NUTS 3). The total quantity of land employed in the production process of a particular agricultural company is adjusted by the land quality. Land quality is expressed as the ratio of the official land price of the j-th region to the maximal official regional land price. That is, the total quantity of land employed in the production process of the i-th company was multiplied by the quality index of the region to which the company belongs. Capital

Table 2. Descriptive statistics of employed variables (1000 CZK)

Variable		Mean	Std. deviation	Minimum	Maximum
Output	y	54 276.60	55 350.40	394.66	862 087.00
Labour	A	95.80	83.33	0.01	1 002.23
Land	L	1 599.46	1 133.74	2.85	9 784.16
Capital	K	59 254.30	62 828.60	5.15	871 205.00
Material	M	30 389.20	33 655.60	114.17	557 210.00

Source: Database Creditinfo Firms' Monitor and our own calculations

Table 3. Development indicators of agriculture in the database (1 000 CZK)

Year	Output	Labour	Land	Capital	Material	Productivity		Intensity	
						labour	land	land	capital
2004	56 184.8	106.07	1 690.4	61 587.5	32 832.1	529.72	33.24	15.94	580.65
2005	55 732.3	97.10	1 597.6	58 726.5	29 734.1	574.00	34.89	16.45	604.83
2006	52 691.0	90.36	1 546.9	57 383.8	29 130.2	583.14	34.06	17.12	635.08
2007	52 705.8	90.71	1 575.7	59 876.5	30 234.6	581.01	33.45	17.37	660.06
Growth rate (%)	–2.11	–5.08	–2.32	–0.93	–2.71	3.13	0.21	2.91	4.37

Source: Database Creditinfo Firms' Monitor and our own calculations is represented by the book value of tangible assets and is deflated by the index of processing (industry) prices (2005 = 100). Finally, the material variable is used in the form of total costs of material and energy consumption per company, and is deflated by the index of processing prices (2005 = 100).

Table 2 gives basic statistical information about the sample. Average output is 55 mil. CZK. Since the standard deviation exceeds the mean of the sample, the variability of output among the companies can be considered large. The minimal and maximal values of the output suggest that there is a big difference between small and large agricultural companies. Nearly analogous comments can be made about the production factors. From these characteristics of the sample, we can deduce that the agricultural companies differ significantly among each other. In other words, we may assume that the firm heterogeneity is highly significant in the sample, and that the use of model specifications that do not allow for capturing the firm heterogeneity might overestimate technical inefficiency.

Table 3 shows that the average growth rate of the output as well as all inputs are negative. Despite this, labour productivity, land productivity, land intensity and capital intensity in the sample increased in the period from 2004 to 2007. These tendencies suggest that agricultural companies are subject to substantial adjustment processes regarding the structure of production factors.

RESULTS

Table 4 presents parameter estimates of the model specifications used. From a comparison of estimated production elasticities, it follows that except for the Truncated BC (Battese and Coelli) model, elasticities do not differ significantly among the model specifications. Therefore, signs and magnitudes of the coefficients, as well as the numerical results, were found to be robust under different model specifications. On the contrary, parameter estimates of the Truncated BC model seem to be biased. The sum of elasticities (except for the Truncated BC model) is in the interval 0.91622 to 0.98554, which suggests slightly decreasing returns to scale. However, it follows from a deeper analysis of the Fixed Management (FM) model that if we include management among the inputs, the average company in the sample is characterized by slightly increasing returns to scale. Thus, the results indicate economies of scale in the sample.

The criteria of theoretical consistency, i.e. the criterion of monotonicity and quasi-concavity for

Table 4. Parameter estimates

	REM	Truncated BC model	"True" FEM	"True" REM	RPM	FM	FMM
Labour (A)	0.19782	0.13079	0.19179	0.20609	0.22430	0.22737	0.24534
Land (L)	0.05449	–0.00956	0.05312	0.07484	0.06410	0.05479	0.03287
Capital (K)	0.07872	0.03475	0.08082	0.08710	0.07585	0.05410	0.04255
Material (M)	0.59435	0.56453	0.59477	0.60630	0.62129	0.63419	0.60727
Return to Scale	0.92538	0.72051	0.92049	0.97433	0.98554	0.97045	0.92802
quasi-concave in A	yes	yes	yes	yes	yes	yes	yes
quasi-concave in L	no	no	no	no	no	yes	yes
quasi-concave in K	yes	yes	yes	yes	yes	yes	yes
quasi-concave in M	yes	yes	yes	yes	yes	yes	yes
Variance and asymmetry parameter							
sigma	0.2952	0.1478	0.3600	0.1324	0.1272	0.1397	0.1406
lambda	2.6064	1.2720	2.9054	1.6892	1.8283	2.4779	2.6135
sigma(u)	0.2756	0.1162	0.3404	0.1139	0.1116	0.1296	0.1313
sigma(v)	0.1058	0.0914	0.1172	0.0674	0.0611	0.0523	0.0502
Log likelihood function	1 603.981	2 093.511	1644.558	1 810.981	1 946.874	2 103.539	2 115.309

Note: $\lambda = \frac{\sigma_u}{\sigma_v}$, $\sigma^2 = \sigma_u^2 + \sigma_v^2$

Source: Own calculations

inputs of the production function, are both fulfilled, at least for the sample mean, only in the Fixed Management model (FM) and Fixed Management model with means (FMM). Whereas monotonicity (a positive slope for inputs) is satisfied in all model specifications, quasi-concavity, i.e., the criterion of the curvature of the production function, is fulfilled only in the FM and FMM models; i.e., only the FM and FMM models do not relax the assumption of diminishing marginal productivity for each input (i.e. $\beta_{qq} + \beta_q^2 - \beta_q < 0$, for $q = A, L, K, M$). This suggests that from a theoretical point of view only the FM and FMM models are applicable to an empirical analysis. On the other hand, the subsequent analysis concerning distinguishing firm heterogeneity in the estimation of technical inefficiency is not relaxed by this theoretical inconsistency. In other words, the theoretical inconsistency does not relax conclusions drawn from the subsequent analysis concerning the estimate of technical inefficiency in the presence of significant firm heterogeneity.

One of the reasons why the criterion of qausi-concavity is not fulfilled in the rest of the model specifications could be the occurrence of the management bias problem. That is, the parameter estimate could be biased if management or other factors that it represents (see Hockmann and Pieniadz /2008/ interpretation of unobserved fixed input in Álvarez et al. /2003/ model) are important inputs in the production process, i.e., in a situation where management has not satisfied the assumption of full separability.

The estimates and statistical significance of the parameter λ point out the significance of technical inefficiency in Czech agriculture. The value of the parameter λ suggests that the variability of output is determined more by the variability of technical inefficiency than by the variability of statistical noise. Thus, we may conclude that inefficiency is a significant phenomenon in Czech agriculture and must be included in the production models. The actual level of technical inefficiency or efficiency, respectively, is subsequently analyzed.

Table 5 provides statistics of estimated technical inefficiency. The Pitt and Lee (1981) Random Effects model (REM) is the first model specification we estimated. This basic specification has several disadvantages or limitations. The main disadvantage or limitation of this model is the assumption that inefficiency (u_i) is time-invariant and not correlated with regressors and statistical noise (v_{it}). Moreover, individual (time-invariant) heterogeneity is part of the estimate of u_i. That is, the model overestimates technical inefficiency in cases where significant firm heterogeneity is present in the sample. Thus, REM serves as a good benchmark in our analysis concerning distinguishing between firm heterogeneity and technical efficiency. The results of the estimate show that in the case of REM, the average level of technical inefficiency in the sample is 0.2194.

The Truncated Bettese and Coelli (1995) (BC) model is the second model specification we used. The BC model partly overcomes the limitations of REM. Technical inefficiency is allowed to change over time. However, u_{it} changes systematically (see $u_{it} = \eta_t u_i = \{\exp[-\eta(t - T)]\}u_i$). Moreover, the heterogeneity is measured by explanatory variables related to the technical inefficiency (see $u_{it} = z_{it}\delta + w_{it}$). We use the following variables in our estimate: land intensity, capital intensity and subsidy per hectare of agricultural land (adjusted by the quality index). However, as mentioned above, the Truncated BC model does not provide an unbiased parameter estimation for our sample. The estimate of technical inefficiency seems to be biased as well. The average technical inefficiency is 0.5559, which seems to be an overestimate when compared to the results of REM. This suggests that the Truncated BC model is not a proper model specification for this sample.

The "True" Fixed Effects model ("True" FEM) allows u_{it} to be time variant; time-invariant heteroge-

Table 5. Statistics of estimated technical inefficiency (u_{it})

	Mean	Std. deviation	Minimum	Maximum
REM	0.2194	0.1396	0.0053	1.4239
Truncated BC model	0.5559	0.3749	0.0161	6.8162
"True" FEM	0.1870	0.0624	0.0601	1.1432
"True" REM	0.0864	0.0472	0.0093	0.8565
RPM	0.0848	0.0472	0.0104	0.8058
Fixed Management (FM)	0.0953	0.0636	0.0126	0.9697
Fixed Management with Means (FMM)	0.0965	0.0652	0.0120	0.9382

Source: Own calculations

neity is captured by a firm-specific intercept. That is, firm (time-invariant) heterogeneity is set apart from technical inefficiency by replacing the intercept by firm dummy variables in the stochastic production frontier function model. Two shortcomings of this model specification were pointed out by Green (2002 and 2003) – the incidental parameter problem and over-specification of the model. The incidental parameter problem is not serious. Green (2002) argues that the bias error is small in the parameter estimation in long panels, and does not determine the estimation of technical inefficiency. The second problem could be more serious. Green (2003) states that if a firm is characterized by persistent technical inefficiency, this becomes a part of the firm-specific constant, and the estimate of technical inefficiency is then underestimated. Table 5 shows that the average technical inefficiency is 0.1870 and the standard deviation is 0.0624 according to the "True" FEM. As we expected, technical inefficiency is lower in the "True" FEM compared to REM. In particular, the variability of technical inefficiency declined. The results show that there are fewer companies with technical efficiency below 70% in "True" FEM than in REM estimates. These characteristics, together with values of fixed effects, suggest that firm heterogeneity is significant in the sample and must be considered in the estimation of technical efficiency.

The "True" Random Effects model ("True" REM) is a reinterpretation of the Pitt and Lee (1981) Random Effects model. It allows for time-variant technical inefficiency, while the firm (time-invariant) heterogeneity is contained in the time-invariant random intercept. Compared with REM, the estimated technical inefficiency decreased significantly. The average technical efficiency is 0.0864, compared to 0.2194 in REM. The variability of technical efficiency is lower as well. We may find a lower frequency of agricultural companies with technical efficiency below 80% in results of the "True" REM, compared to REM. This again points to significant firm heterogeneity in the sample. Furthermore, the significant difference between "True" FEM and "True" REM might be caused by the incidental parameter problem, due to the short and unbalanced panel data set and large number of agricultural companies. The short and unbalance panel data set might cause lots of fixed effects to be inconsistent. Thus, the incidental parameter problem seems to be serious in our case. Moreover, the over-estimation problem can also arise for this reason.

The "True" Random Effects model is a special case of the Random Parameters model (RPM). RPM also allows for randomness next to the intercept for other coefficients. The close relationship between "True" REM and RPM can also be seen in the results. The estimates of technical inefficiency are almost identical. The average of technical inefficiency is 0.0848 and its variance is 0.0472.

The fixed management model (FM) is a Random Parameters model with an unobservable fixed input representing management (see Álvarez et al. 2003 and 2004). According to Hockmann and Pieniadz (2008), this unobservable fixed input represents, next to management, differences in the quality of factors (inputs) such as climatic conditions, quality of land, etc. Thus, the unobservable fixed input is an unobservable firm-specific factor representing the environment and conditions of the production process. Table 5 provides the statistics of technical inefficiency in the FM model. These statistics are very close to the "True" REM and RPM. That is, the average of technical inefficiency is 0.0953 with variance 0.0636, which is at a significantly lower level than REM. Thus, the same conclusions about the significance of firm heterogeneity in the sample can be made. Nearly the same results are obtained in the estimation of the Fixed Management model with means (FMM). The FMM model contains the Mundlak

Table 6. Correlation of technical efficiency

	REM	Truncated BC m.	"True" FEM	"True" REM	RPM	FM	FMM
REM	1.0000	0.7179	0.0756	0.2528	0.2282	0.2853	0.2795
Truncated BC m.		1.0000	0.1404	0.2403	0.2167	0.2604	0.2587
"True" FEM			1.0000	0.9367	0.9409	0.9020	0.9029
"True" REM				1.0000	0.9725	0.9401	0.9366
RPM					1.0000	0.9463	0.9447
FM						1.0000	0.9969
FMM							1.0000

Source: Own calculations

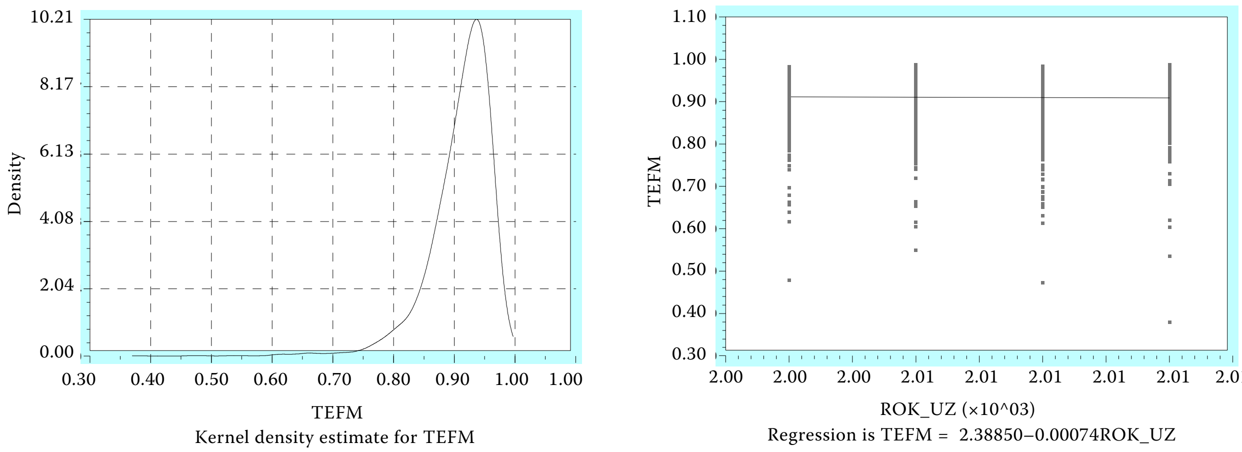

Figure 1a, b. Technical efficiency – Fixed Management Model (FM)

Source: Own calculations

specification of the optimal level of management (see Álvarez et al. 2004). The Mundlak specification controls for a potential problem with the correlation of optimal management with other inputs. However, the results show that this problem is not present in our estimates (see nearly identical estimates).

Table 6 provides information about the correlation of technical efficiency between estimated model specifications. The correlation coefficients show that a very low correlation can be found between model specifications with unmeasured firm heterogeneity (i.e. "True" FEM, "True" REM, RPM, FM and FMM) and REM. On the contrary, the differences in estimated technical efficiency seem to be very low among the models with unmeasured firm heterogeneity, since the correlation coefficient is above 0.9 in all cases. The same results are obtained if we use the Spearman rank correlation coefficient.

To sum up, the results suggest that superior estimation of technical efficiency is provided by the family of Random Parameters models for our sample, due to the significant presence of firm heterogeneity. "True" FEM is not a proper specification due to the occurrence of the incidental parameter problem, which is the result of a short and unbalanced panel data set with a large number of agricultural companies. Moreover, taking into account the theoretical consistency of the stochastic frontier production function model, i.e., assumptions regarding the slope and curvature of the production function, the proper model specification for the estimation and analysis of technical efficiency seems to be the Fixed Management model.

Figure 1a and 1b show the distribution of technical efficiency in the sample, taken from the estimate of the Fixed Management model. The kernel density estimator (Figure 1a) illustrates that the majority of agricultural companies have technical efficiency higher than 80%. The technical efficiency in the sample is, on average, 90%. Figure 1b suggests that there are few differences in the distributions across years in the sample.

CONCLUSIONS

An analysis of the estimated stochastic frontier production function models confirmed the assumption of significant firm heterogeneity in the sample. It was demonstrated that REM significantly overestimates technical inefficiency. Therefore, only those model specifications which allow for the capture of time-invariant firm heterogeneity may provide consistent estimates of technical efficiency. In our analysis, the family of Random Parameters models provided superior specifications for the estimation of technical efficiency. Taking into account the theoretical criteria of the production function, the Fixed Management model was chosen as the best model specification, and the one which should be used for the measurement and analysis of technical efficiency in the sample.

The second question that was posed in the introduction concerns the level of technical efficiency. Since the sample can be regarded as representative of agricultural companies, we may state based on the results that technical inefficiency is a significant phenomenon in Czech agriculture. The average level of technical efficiency is around 90% for agricultural companies. Considering that technical efficiency is an important determinant of the competitiveness of Czech agricultural companies, ways must be found to reduce the waste of resources due to inefficient use of inputs.

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