Efficiency and heterogeneity in Czech food processing industry

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1 Introduction

In this paper we analyze productivity in the Czech food processing industry. Our aim is to conduct a comparative analysis among the different industries, and identify the productive and less productive companies in Czech food processing. In addition, we will analyse whether these companies are concentrated in individual sectors only or spread across all branches. Based on a joint estimation of sector-specific production functions, we will focus less on all the various sources of factor productivity and their development over time (this analysis was carried out in Čechura, Hockmann 2010), and concentrate mainly on the development of the technical efficiency of companies in different food processing industries. Thus, we will conduct an analysis of the intra- and intersectoral differences in technology and efficiency in the Czech food processing sectors. Technical efficiency, as an integral part of overall economic efficiency, is an important indicator of the competitiveness and productivity of companies, since it provides information on the extent to which they could increase the productivity of their inputs by catching up to the best performing companies in a sector, and thereby improve the competitiveness of the whole value chain.

This analysis is related Čechura and Hockmann (2010), who investigated the determinants of productivity and efficiency on the sectoral level. We complement their work on differences between sectors with an analysis of the variation within a sector. In particular, two main questions will be elaborated upon in this paper. First, since the differences among food processing companies and food processing sectors could be significant in terms of firm heterogeneity and sector-specific technology, we will examine an appropriate model specification for distinguishing firm- and sector-level efficiency and heterogeneity. The second question concerns the significance of technical efficiency and the sectoral differences in technical efficiency. Since the Czech agrarian sector has experienced a number of important institutional and economic changes in recent decades, it is now an appropriate time to ask how well inputs are used and how technical efficiency has contributed to the competitiveness of food processing companies.

The paper is organized as follows: Chapter 2 contains the theoretical background of the paper and presents the estimation strategy; Chapter 3 describes the data set; Chapter 4 presents results of different econometric specifications, compares the fitted models, discusses their differences and points out the preferred specification, which is then used for an analysis of heterogeneity and technical efficiency in the chosen food processing industries; and Chapter 5 contains a discussion and concluding remarks, including policy recommendations.

2 Theoretical considerations

2.1 Economic background

We assume that companies maximise their net sales ratio subject to a technical constraint which is given by the production possibilities (Georgescu-Roegen 1951, Kumbhakar 2010). The main reason we depart from conventional profit maximisation is that in our model we allow for variable returns to scale, assuming that all inputs are flexible. Profit maximisation is only reasonable if at least one of two requirements is fulfilled. First, there are fixed inputs which are remunerated by short run profits. Second, the technology exhibits constant returns to scale so that all revenues can be used for remuneration of the inputs. Under decreasing returns to scale, there is excess revenue that is not redistributed to the inputs, while under increasing return to scale, the revenue will not be sufficient to compensate all inputs with their marginal product. The assumption of maximising net sales profits overcomes the problems involved in simple profit maximisation.

We follow Kumbhakar (2010) and assume that the production possibilities can be represented by a translog transformation function:

$$\ln f(\mathbf{x},y)=\alpha_y \ln \mathrm{y}+\frac{1}{2}\alpha_{yy}\mathrm{lny}^2+\sum_j \alpha_j \ln x_j+\frac{1}{2}\sum_j\sum_k \beta_{jk}\ln x_j \ln x_k + y\sum_j \delta_j \ln x_j = 0 \quad (1)$$

Here x and y denote inputs and outputs, respectively. If the transformation function is normalized by the restrictions

$$\sum_j \beta_j = 1, \quad \sum_j \beta_{jk} = 0 \ \forall k \quad and \quad \sum_j \delta_j = 0 \qquad (1a)$$

the input distance function is obtained. This function will play a central role in the empirical application.

Technical efficiency is introduced by a proportionality factor, $e^u > 1$, which indicates how much output can be increased without changing the bounds of the transformation function. In addition, we consider the factor A which captures systematic (α_0) and stochastic shifts (v) of the function, i.e., $A = \alpha_0\, e^v$.

Denoting the prices for input and outputs by w and p the optimisation problem is:

$$\max_{y,\mathbf{x}}\left\{\frac{p\,y-\mathbf{w}'\mathbf{x}}{\mathbf{w}'\mathbf{x}};\, A\, f(\mathbf{x},y^*)=1\right\}, \text{with } y^* = ye^u . \qquad (2)$$

After some transformation the first order conditions become:

$$\frac{p\,y}{\mathbf{w}'\mathbf{x}}+\lambda\, A\, f(\mathbf{x},y^*)\frac{\partial \ln f(\mathbf{x},y^*)}{\partial \ln y^*}=0 \qquad (3a)$$

$$\frac{p\,y}{\mathbf{w}'\mathbf{x}}\frac{w_j x_j}{\mathbf{w}'\mathbf{x}}+\lambda\, A\, f(\mathbf{x},y^*)\frac{\partial \ln f(\mathbf{x},y^*)}{\partial \ln x_j}=0 \qquad (3b)$$

where λ represents the Lagrange multiplier. Conditions (3a) and (3b) together imply:

$$\frac{\partial \ln f(\mathbf{x},y^*)}{\partial \ln y^*}=\sum_j \frac{\partial \ln f(\mathbf{x},y^*)}{\partial \ln x_j}$$

or in terms of the transformation function (1):

$$\alpha_y+\alpha_{yy}\mathrm{lny}^*+\sum_j \delta_j \ln x_j = \sum_j \beta_j + \sum_j\sum_k \beta_{jk}\ln x_j + \lambda y \sum_j \delta_j \qquad (4)$$

After applying the restrictions (1a) and normalising by x_1, (4) reduces to:

$$\alpha_y+\alpha_{yy}\mathrm{lny}^*+\sum_{j\neq 1}\delta_j \frac{\ln x_j}{\ln x_1}=1 \qquad (4a)$$

which holds for every x and y only when α_y = 1, α_{yy} = 0, and $\delta_j = 0\ \forall j$. Using these restrictions together with those in (1a) in the transformation function gives:

$$\ln\frac{x_1}{y}=\alpha_0+\sum_{j\neq 1}\alpha_j \ln\frac{x_j}{x_1}+\frac{1}{2}\sum_{j\neq 1}\sum_{k\neq 1}\beta_{jk}\ln\frac{x_j}{x_1}\ln\frac{x_k}{x_1}+u+v \qquad (5)$$

Equation (5) can be estimated using standard stochastic frontier techniques. The virtue of (5) is that it only requires information on quantities, and also complies with the conditions of economic optimisation. Moreover, given the specification of the error term (v) and the efficiency parameter (u) there is no endogeneity problem involved in the estimation (on the endogeneity problem, see Marschak and Andrews (1944), Olley and Pakes (1996) and Levinsohn and Petrin (2003)).

2.2 Productivity, heterogeneity and efficiency

Productivity finds its expression in the shape of (5), and thus the parameter vector ($\boldsymbol{\alpha}$, $\boldsymbol{\beta}$). However, the coefficients depend on the quality of the individual inputs. Input quality, in turn, is determined by the embedded knowledge, i.e. human capital for labour, technological knowledge for capital, and embedded innovation in materials (Barro and Sala -I- Martin, 1995). Due to technological progress and learning by doing, the technology improves over time. This will induce not only shifts in the transformation function but will also affect the productivity of the individual inputs. Moreover, it can be assumed that the various improvements in quality have rather different direct and indirect effects on the individual inputs. However, due to limitations in data availability, the impacts for the various improvements cannot be estimated separately. Instead, it is commonly assumed that a trend variable (*t*) can be incorporated which captures the joint effects in input quality improvements. We proceed in the same way and extend (5) by:

$$\alpha_0 = b_0 + b_t t + \frac{1}{2}\beta_{tt} t^2$$

$$\alpha_j = b_j + \beta_{jt} t, \forall j$$

The resulting function:

$$\ln\frac{x_1}{y} = b_0 + b_t t + \frac{1}{2}\beta_{tt} t^2 + \sum_{j\neq 1} b_j \ln\frac{x_j}{x_1} + \sum_{j\neq 1}\beta_{jt} t \ln\frac{x_j}{x_1} + \frac{1}{2}\sum_{j\neq 1}\sum_{k\neq 1}\beta_{jk}\ln\frac{x_j}{x_1}\ln\frac{x_k}{x_1} + u + v \qquad (6)$$

will be used as a benchmark in the empirical application. The panel structure of the data set is considered by estimating a random effect model (Pitt and Lee 1981). Within this framework, it has to be assumed that the efficiency term *u* is allowed to vary among firms but not over time. This implies that the shocks which induce inefficiency have to be the same in each period, and that the firms are not able to adjust to these shocks. An obvious extension is to allow for time-varying inefficiency. This results in the "true random effect" model discussed in Greene (2004). Within this context, the parameter b_0 is allowed to vary among firms.

The specification discussed so far presumes that firms have similar technologies, and the only differences result from the intensity of input use. This implies that firms from different sectors but with the same input-output combination generate the same marginal products. Given the diversity of the food processing sector, this implication can be regarded as rather strong. We therefore assume that heterogeneity exists not only among sectors, but also among the firms within a sector. We consider these two kinds of heterogeneity by expanding the first order terms in (6) (*Note: the true effect model results from (7) by assuming that* b_t *and all* b_j *are constants and all* β_s *are zero*):

$$\begin{aligned} b_0 &= \beta_0 + \sum_s d_s\beta_s + \beta_\eta\eta, \\ b_t &= \beta_t + \sum_s d_t\beta_{st} + \beta_{t\eta}\eta, \\ b_j &= \beta_j + \sum_s d_s\beta_{js} + \beta_{j\eta}\eta, \forall j \end{aligned} \qquad (7)$$

In (7), *d* represents dummy variables which account for intersectoral differences in technologies. In the empirical application, we distinguished between six sectors (slaughtering, dairy, milling, feedstuffs, beverages, and others). The variable η represents an unobservable random variable which is assumed to capture technology differences among firms which are not covered by the dummy variables. We assume that η is the same for all parameters, so that there is only one firm-specific effect. In the estimation, we assume that η follows a standard normal distribution, i.e., $\eta \sim N(0,1)$. The specification given by (6) and (7) can be estimated using a random parameter approach. In the context of efficiency analysis, this class of models was introduced by Tsionas (2002) and Greene (2005).
The preceding discussions consider only the intra- and intersectoral heterogeneity of the transformation function. However, the efficiency term may also be subject to heterogeneity.

We experimented with various specifications in the spirit of Battese and Coelli (1995); however, the estimator did not converge, and we opted for an alternative approach. Following Hadri (2003), we assumed that *u* is heteroscedastic and that the sector dummies could be used to account for this phenomenon. Even though the error terms have no direct impact, the determinants of heteroscedasticity still influence the expected value of the inefficiency term. Efficiency is estimated using the Jondrow et al. (1982) procedure. This approach computes $E[u| u + v]$, i.e., expected inefficiency under the condition that $u + v$ is given. The density and distribution function of $u + v$ are used in the calculation; however, these depend on the variances of *u* and *v*, and so does $E[u| u + v]$.

Given these considerations, the estimation technique can be summarized as:

$$\ln \frac{x_{1t}}{y_t} = g(\mathbf{x}_{it}^*, t, \mathbf{d}, \eta_i) - u_{it} + v_{it}, \text{ with}$$
$$v_{it} \sim N(0, \sigma_v^2) \tag{8}$$
$$u_{it} \sim \mathrm{N}^+(0, \sigma_s^2) \text{ and } \sigma_s^2 = \sigma_u^2\, e^{\sum_s d_s \gamma_s}$$
$$\eta_i \sim \mathrm{N}(0,1).$$

Here the function g(•) captures all influences discussed using (6) and (7). The matrix **d** represents the sector dummies, and **x*** contains the transformed right-hand-side variables in (6). The subscripts *i* and *t* denote firm and time, respectively.

3 Data set

The data 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 details 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.

The panel data set that we use in our analysis contains companies whose main activity is food processing according to the OKEČ classification (OKEČ is a basic classification of economic activities in the Czech Republic and is processed in accordance with the rules for creating sector classifications in EU member states). It is an unbalanced panel data set, which represents the period from 1998 to 2007 and contains, before the cleaning process, 1,375 food processing companies with 6,473 observations. Since not all companies in the database have complete information, and some observations can be regarded as outliers, we exclude those companies with negative and zero values of the variables of interest. Moreover, we exclude companies whose labour productivity is lower than 150 000 CZK since these companies are regarded as non-productive. We also exclude the upper percentile of labour productivity to remove outliers. Finally, we include in our sample only those companies having three or more final accounts. Thus, we were constrained to using an unbalanced panel data set containing 512 food processing companies with 2,612 observations, i.e., on average 5.1 observations per company in the period from 1998 to 2007.

The following variables were used in the analysis: output (y_{it}), labour (A_{it}), capital (C_{it}) and inputs (material) (M_{it}). Output represents the total sales of goods, products and services of the company. Labour input is total personnel costs per firm (including health and social insurance) divided by annual average gross wage in the region where the company is located. The source of regional wages is the Czech Statistical Office (since only the period 2002 – 2006 is covered, the wages in other years were approximated according to changes in the index of average wage growth in the Czech Republic). Capital represents the book value of tangible assets. Finally, variable inputs (materials) were used in the form of total costs of materials and energy consumption per firm. Output was deflated by the index of food processing prices (2005 = 100) and capital, and inputs were deflated by the index of processing prices (2005 = 100).

4 Results

In the estimation, we normalized all variables in logarithm by their sample mean. This has the advantage that the first order parameters can be interpreted as cost shares at the mean. We used this procedure since it significantly simplifies the discussion of the estimates.

4.1 Model selection

Table 1: Model selection

	REM	True REM	RPM	RPM with sector dummies	RPM with sector dummies and heteroscedasticity
Model	5	4	3	2	1
Restrictions	4 + $\beta_\eta = 0$,	3 + $\beta_{t\eta} = 0$, $\beta_{j\eta} = 0$,	2 + $\beta_s = 0$, $\beta_{st} = 0$, $\beta_{js} = 0$	$\gamma_s = 0$	
Number of parameters	12	13	16	36	41
Log likelihood function	-57.04	72.4	589.1	657.7	898.8
LR test Probability		258.9 < 0.001	1033.4 < 0.001	137.2 < 0.001	482.2 < 0.001
Mean of inefficiency	0.355	0.180	0.1672	0.138	0.130

Note: REM - Random effect model, True REM - True random effect model, RPM - Random parameter model
Source: our own calculations

We first discuss the question of whether a model formulation as flexible as that provided in (8) is an appropriate choice for Czech food processing. Since the alternative formulations are presented in (8) (the corresponding restrictions are given in Table 1), we tested whether the more flexible formulations contribute to the explanatory power of the model. We conducted the tests by comparing a model to the next most flexible formulation.

The LR test establishes that the more flexible a specification is, the better it represents the production structures in Czech food processing. Thus we conclude that the model given by (8) is the most appropriate formulation. Moreover, Table 1 shows that the increase in flexibility reduces the mean of inefficiency. Thus, as expected, the more flexibly the production structures are modelled, the more the variation of output is explained by the transformation function, and the less significant inefficiency becomes.

Given the results of the likelihood ratio test, in the rest of the paper we will consider only the parameter estimates of RPM with sector effects and heteroscedasticity. Parameter estimates are provided in Table 2. The table is organised as follows: first, a distinction was made between the effect on efficiency and the transformation function; then, the parameter of the transformation function was separated into second- and first-order effects, and the latter separated again into inter- and intrasectoral effects.

Table 2: Parameter estimates

			Coefficient		Standard error	z-Value
First order effects	Constant	β_0	-0.045	***	0.005	-8.610
		$\beta_{0\_slaughter}$	0.089	***	0.008	11.680
		β_{0_dairy}	-0.026	**	0.012	-2.070
		$\beta_{0\_milling}$	0.068	***	0.014	4.920
		$\beta_{0\_feedstuffs}$	0.237		128.944	0.000
		$\beta_{0\_beverages}$	-0.217	***	0.010	-22.560
		$\beta_{0\eta}$	0.076	***	0.004	17.310
	Time	β_t	-0.025	***	0.002	-11.190
		β_{TT}	-0.004	***	0.001	-2.610
		$\beta_{t\_slaughter}$	0.011	***	0.004	3.140
		β_{t_dairy}	-0.002		0.005	-0.340
		$\beta_{t\_milling}$	0.012		0.009	1.330
		$\beta_{t\_feedstuffs}$	0.007		0.005	1.520
		$\beta_{t\_beverages}$	-0.002		0.005	-0.500
		$\beta_{t\eta}$	0.001		0.001	0.430
	Capital	β_k	-0.038	***	0.003	-13.560
		β_{KT}	0.004	***	0.001	4.050
		$\beta_{k\_slaughter}$	-0.059	***	0.006	-10.090
		β_{k_dairy}	0.009		0.008	1.100
		$\beta_{k\_milling}$	-0.043	***	0.013	-3.470
		$\beta_{k\_feedstuffs}$	0.000		0.006	-0.040
		$\beta_{k\_beverages}$	-0.035	***	0.006	-5.400
		$\beta_{k\eta}$	0.073	***	0.002	46.890
	Materials	β_v	-0.732	***	0.004	-185.020
		β_{VT}	-0.003	***	0.001	-3.010
		$\beta_{v\_slaughter}$	0.078	***	0.008	9.670
		β_{v_dairy}	0.056	***	0.010	5.440
		$\beta_{v\_milling}$	0.020		0.017	1.150
		$\beta_{v\_feedstuffs}$	0.001		0.008	0.110
		$\beta_{v\_beverages}$	0.086	***	0.009	9.600
		$\beta_{v\eta}$	0.219	***	0.003	77.960
Second order effects		β_{KK}	-0.032	***	0.001	-22.910
		β_{VV}	-0.166	***	0.003	-60.060
		β_{KV}	0.039	***	0.002	25.400
Error terms	Efficiency	σ_u	0.849	***	0.032	26.620
		$\gamma_{slaughter}$	-0.661	***	0.037	-17.790
		γ_{dairy}	0.431	***	0.021	20.060
		$\gamma_{milling}$	-0.198	***	0.026	-7.480
		$\gamma_{feedstuffs}$	-10.939		4376000	0.001
		$\gamma_{beverages}$	0.701	***	0.019	36.010
		σ_v	0.081	***	0.002	50.630
		σ_u/σ_v	2.511 (estimated with mean of σ_u)			

Source: own estimates; ***, **, * denotes significance at the 1%, 5%, and 10% level, respectively

We start by discussing some general characteristics of the estimates. First, as could be expected from the results of the model comparisons, most of the estimated parameters are highly significant. This concerns not only those conventionally discussed in production function estimates, but also holds for most of the coefficients which capture inter- and intrasectoral heterogeneity. Thus, we can already conclude that heterogeneity among firms as well as among sectors is an important characteristic in Czech food processing, and has to be considered when conducting a reliable analysis of the sector. This is true for production technology as well as technical efficiency. The latter finds its expression in the highly significant impact the sector dummies have on heteroscedasticity.

The estimation results can furthermore be evaluated by checking whether the theoretical consistency of production technology is fulfilled. Specification (1) and the restrictions in (1a) imply the estimation of an input distance function. Thus, even though we use a further restriction, the functional form in (5) should inherit the properties of an input distance function. Färe and Primont (1995) show that this representation of production technology needs to be non-increasing in outputs, as well as non-decreasing and concave in inputs. Given that we have estimated the negative of an input distance function, the monotonicity requirements for inputs results in $\beta_K < 0$, $\beta_V < 0$ and $\beta_K + \beta_V > -1$. Table 2 shows that these conditions are met, even if intersectoral heterogeneity is considered. Diminishing marginal returns (concavity) in inputs requires in our case $\beta_{qq} + \beta_q^2 - \beta_q > 0$ for q = K, L, V. This condition holds for all inputs[1]. The monotonicity requirement for output is fulfilled too, because restriction (4a) was directly applied.

The estimated cost shares correspond to the information we have in the data set. The most significant part of company expenditures is for materials. This was expected since the procurement of agricultural raw materials usually constitutes the majority of the cost in the food processing industry (Plášil, Mezera, et al., 2010). However, significant differences in both sector and firm were revealed by the estimates. While in the case of materials the corresponding expenditure is lower in the selected industries, the cost share of capital is generally higher if the parameter is significant. Intersectoral effects were present for both inputs. However, their influences were much more pronounced for material inputs than for capital. One reason for this result is the different bargaining positions of the food processors in the relevant markets. The conditions on credits are determined to a large extent by the macroeconomic environment, and processors have only limited opportunities to negotiate for better conditions. Moreover, the majority of banks do not distinguish between food processing sectors as far as the sector risk premium is concerned. That is, they take the food processing industry as one sector and score the company as a food processing company. In contrast, the situation is different for agricultural raw materials. The prices are usually defined in bilateral negotiations between farmers and processors. Moreover, if markets do not function perfectly, there is a wide range of price variations, depending on the bargaining power of the individuals involved in the transaction. Finally, the markets for raw materials differ significantly between the sectors in terms of market structure and size.[2]

In addition, we found that technical change had a strong impact. On average, the production possibilities increased by 2.5% per year. Moreover, technical change slightly accelerated in the period under investigation. However, there were neither significant sector-specific nor firm-specific effects. This suggests that the improvement of production possibilities was due more to the diffusion of knowledge generated in another part of the economy or imported

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[1] Here we restrict our attention to the first principle minors of the second derivative of the input distance function. Reason: too time-consuming to test everything and in addition, we do not need convex technologies (which imply diminishing returns to scale), but only diminishing returns to scale (which does not imply convex technologies).

[2] Several studies have shown that there is friction in market exchanges in the Czech Republic; see, e.g., Bečvářová 2008, Čechura, Šobrová 2008; and Lechanová 2006.

from abroad than to the sector's own research and development.[3] Since all companies had to comply with the acquis communautaire, significant investment was needed in all sectors. On the one hand this explains the relatively high impact of technical progress on the period under investigation. On the other hand, the compliance process can be regarded as one reason why productivity changes were mainly homogeneous among sectors and companies. In addition, the estimates for biased technical change (β_{KT} and β_{VT}) are significant but rather small. This suggests that technical change was predominately Hicks neutral.

4.2 Heterogeneity in production structures

Table 2 shows that there are significant differences in the cost shares between and within sectors. However, since the unobserved component captures all firms, the estimation results provide no information about whether the differences in cost shares, the management effect or the impact of technical change among sectors finds expression in the technologies of the individual companies. This implies that it is not possible to assess whether company productivity is the result of a sectoral effect or whether it is a consequence of its individual decision-making processes, organisation or management.

Nevertheless, this question can be analysed by separating the total variance of the indicators into a component which captures their variance within each sector, and a component that captures the variance between industries (Table 3). With regard to the constant, we found that about one-third of the total variance results from the variance among companies within an industry. Thus, intersectoral differences in technologies are more pronounced than intrasectoral differences. However, this result was expected because of the various characteristics of the production processes in the selected food industries. Only the beverage industry and the group that captures other sectors show a high within-group variance. This result is consistent given the heterogeneous composition of these groups (for instance: brewery, mineral water, etc., for the beverage industry).

Given the estimates in Table 2, it is not surprising that the impact of technical change shows no pronounced intra- or inter-industry effects. The conclusions for the cost shares of capital and materials as well as for management are similar – however, the effects are much more pronounced. Almost all the variation in these indicators is due to intrasectoral differences. With regard to management, this suggests that there is a significant gap between the best firms and worst firms in the selected sectors. This implies that there are large differences, especially in input quality and corporate governance, between the firms within the industries. In addition, the large intrasectoral differences might also be caused by the fact that the small firms are of a family nature, and hence differ significantly from large companies. Moreover, the finding has an important implication: The differences in the management variable suggest that the food processing industry will be subject to accelerated structural change in the near future. In particular, this development will be expressed in a significant number of exits from the market.

Consistent with the conclusion derived from Table 2, the cost share of capital has a higher variance than the cost share of materials. Moreover, for these two indicators we also observe that the intrasectoral variance is more pronounced than the intersectoral variance. Again, this implies that access to the capital market and the procurement of raw materials is governed almost totally by company, and to a lesser extent by industry, characteristics. Moreover, this

[3] In fact, R&D expenditures in the sectors are rather small, and only a very small number of firms are conducting R&D at all. This can be deduced from the low level of investment in intangible property (see Panorama of Food Processing Industry for the years 2000–2007, MZe, Prague).

finding supports the conclusions regarding the raw material and capital market provided in Section 4.1.

Table 3: Variance decomposition of cost shares

	Constant	Time	Capital	Materials	Management
Slaughtering	0.00605	0.00003	0.00905	0.05374	1.04782
Dairy	0.00449	0.00003	0.00791	0.05522	0.77739
Milling	0.00376	0.00002	0.00766	0.02596	0.65177
Feedstuffs	0.00313	0.00003	0.00218	0.06877	0.54182
Beverages	0.01917	0.00004	0.02153	0.14939	3.31979
Others	0.01205	0.00004	0.01422	0.08814	2.08748
Within-group variance	0.01038	0.00004	0.01268	0.08598	1.79827
Between-group variance	0.01914	0.00002	0.00144	0.00539	0.15795
Total	0.02953	0.00006	0.01412	0.09138	1.95622
Share of within-group variance	35.2%	63.6%	89.8%	94.1%	91.9%

Source: Own calculations

4.3 Heterogeneity in Efficiency

The preceding discussion captures the inter- and intra-industry difference that occurs on the production frontier, i.e., that firms fully exploit their production possibilities. However, due to stochastic and systematic effects, output may be somewhat below the upper limit. The various reasons for inefficiency are not presented here[4]. We will deal instead with other related questions: (1) Are there pronounced efficiency differences among sectors? (2) How did the intra-industry level of efficiency develop over time? In particular, do we observe falling-behind or catching-up processes within industries? (3) Is the relative position of the companies stable over time?

The answers to the first question are given in Figure 1. The graphical illustration shows that some features are common for all sectors. First, in each sector the best companies have a high technical efficiency, which is stable over time. The same holds for the mean of technical efficiency. If we compare the level of mean technical efficiencies (Slaughtering 0.864; Dairy 0.875; Milling 0.892; Feedstuffs 0.882; and Beverages 0.888) within the sector, we can conclude that, on average, companies greatly exploit their production possibilities. On the other hand, the developments in minimum technical efficiency differ among the sectors, and suggest that structural change will have a different power and speed in selected industries. While a decrease in technical efficiency may indicate a loss of market position (which is connected with growing imports), an increase can be interpreted as the growing strength of Czech companies.

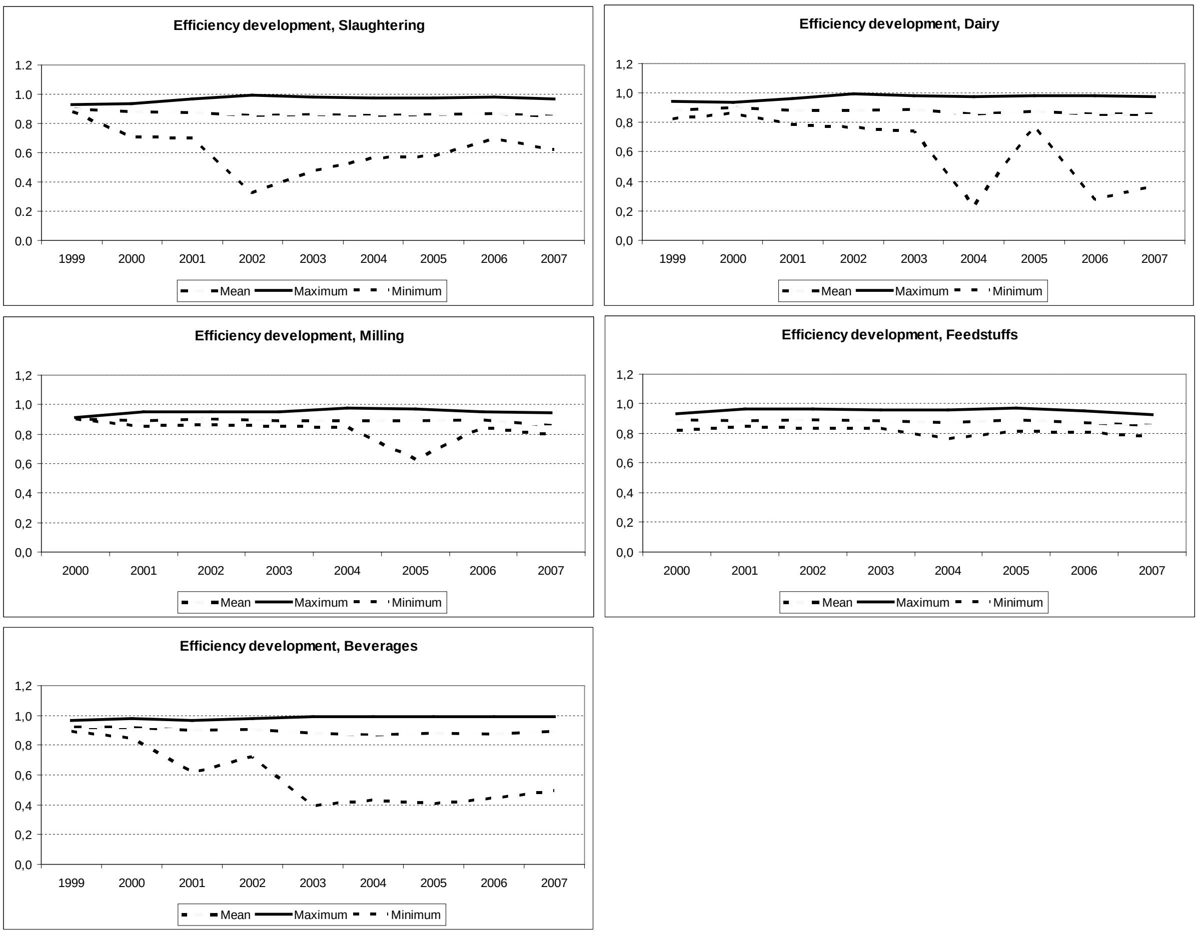
Moreover, since the mean technical efficiency is high and close to the maximum technical efficiency, a drop in competitiveness would suggest a decrease in sector size. Finally, the difference between the best and average company is constant over time, whereas the difference between the best or average company, respectively, and the worst company increased (feedstuffs is an exception). This suggests that some companies are falling behind. They may not be able to keep pace with competitors. This might be an indication of accelerated structural changes in sectors in the coming years.

The information presented in Figure 1 does not allow for a definitive conclusion concerning which firms will be subject to structural change. If technical efficiency is highly volatile due to leapfrogging and falling-behind processes for each company, market exit may occur

[4] See, e.g., Latruffe et al. 2004; Bokusheva, Hockmann 2006; Davidova, Latruffe 2007; Hockmann, Pienadz 2008.

randomly, and predictions about industry development will not be possible. However, if instead the position or rank of the companies is stable, verifiable statements regarding structural change are possible.

Figure 1: Efficiency development



Source: own calculations

Table 4: Spearman’s rank correlation coefficients of technical efficiency

	2000/01	2001/02	2002/03	2003/04	2004/05	2005/06	2006/07
Slaughtering	0.829	0.739	0.792	0.865	0.925	0.884	0.807
Dairy		0.700	0.867	0.733	0.790	0.757	0.746
Milling	Insufficient observations	0.855	0.876	0.540	0.525	0.537	0.592
Feedstuffs		0.697	0.907	0.809	0.871	0.922	0.797
Beverages	0.864	0.772	0.789	0.798	0.800	0.838	0.814
Other	0.776	0.823	0.833	0.843	0.868	0.828	0.848

Source: own calculations

The question of stability can be analysed using the figures provided in Table 4, which provides the Spearman’s rank correlations of technical efficiency in selected sectors. Since the order of companies in the industry is quite stable, leapfrogging does not appear to be a particularly common phenomenon in the selected industries. Thus, structural change occurs in a way such that the most successful companies strengthen their position. Companies with poor performance are not able to catch up with the developments of the industry leaders, and are therefore falling more and more behind. One exception is Milling, in which leapfrogging cannot be denied. Together with the small difference between the maximum and minimum technical efficiency in the majority of years, this suggests that the market environment is tough, and that companies compete for the best position by reducing the waste of resources.

In addition, we analysed how technical efficiency is related to company technologies. In doing so, we calculated Pearson correlation coefficients between efficiency and the various indicators of technology (i.e., elasticities) presented in Table 2. For none of the inputs were we able to find any significant correlation within the sectors. However, this suggests that performance can be regarded as independent from the chosen production technology, and is mainly the consequence of management failures in the companies.

4. Discussion and concluding remarks

In this section we will concentrate on the question raised in the introduction, namely the one regarding distinguishing firm- and sector-level efficiency and heterogeneity, as well as the second question concerning the significance of technical efficiency, and how technical efficiency contributes to the competitiveness of food processing companies.

First of all, the estimates of the production function suggest that heterogeneity among firms, as well as among sectors, is an important characteristic of Czech food processing. This holds true for production technology as well as technical efficiency. As far as estimated cost shares are concerned, significant sectoral and company differences were revealed by the estimates. Intersectoral effects were much more pronounced for material inputs than for capital, suggesting the different bargaining positions of food processors in the relevant markets. In addition, we found that technical change had a strong impact, which was neither sector- nor firm-specific and predominately Hicks-neutral.

The decomposition of total variance of the constant showed that intersectoral differences in technologies are much more pronounced than intrasectoral ones. However, for the cost shares of capital, materials and management, the opposite is true. We found a significant gap between the best firms and worst firms in the selected sectors. According to the differences in the management variable, this suggests that the food processing industry will be subject to accelerated structural change in the coming years.

As far as technical efficiency is concerned, we may conclude that, on average, companies greatly exploit their production possibilities. On the other hand, some companies are falling behind and cannot keep pace with competitors. Since developments differ among sectors, we may anticipate that the expected structural change will have different powers and speeds among the selected industries. Moreover, since leapfrogging does not appear to be present in the selected industries, structural change occurs in a way such that the most successful companies strengthen their position. Companies with poor performance fall farther and farther behind. One exception is Milling. We were able to find tough competition for the best position in this industry.

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