Heterogeneity in Technology and Efficiency – Specifics of the Food Processing Industry in the Visegrád Countries

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Paper prepared for presentation at the EAAE 2014 Congress
'Agri-Food and Rural Innovations for Healthier Societies'

August 26 to 29, 2014
Ljubljana, Slovenia

Abstract: The paper analyses the food processing industry in Visegrád countries. In particular, it deals with the analysis of heterogeneity in technology and efficiency. The introduced theoretical framework allows to capture inter- and intrasectoral differences in technology as well as the country specifics. The results show that both intersectoral heterogeneity and heterogeneity among firms are an important characteristic of EU food processing industry. Moreover, the country specific effects were pronounced for Czech, Hungarian and Polish dairy sector, Czech feedstuff sector, Polish, Hungarian and Slovak slaughtering sector. Moreover, we found that on average the food processing companies highly exploit their production possibilities. However, some food processing companies are falling behind. This holds for Slaughtering and Dairy sector in all Visegrád countries.

Keywords: Visegrád countries, food processing, heterogeneity, technology, efficiency.

JEL classification: D 24, O 12, P 27

Acknowledgements: The publication was generated as part of the COMPETE Project, Grant Agreement No. 312029 (http://www.compete-project.eu/), with financial support from the European Community under the 7th Framework Programme.

1 Introduction

The food processing industry is an important and integral part of the agri-food chain. A competitive food processing industry is especially important for the agricultural sector. In particular, only productive and competitive food processors can create a high demand which can be met by the domestic agricultural sector. Ten years after the enlargement of the EU, the question arises of how the food processing industry in Visegrád countries fulfils this role. In particular, have the food processing companies taken advantage of common market opportunities or are they falling behind? Are the food processing sectors in Visegrád countries subject to subsequent structural changes?

This paper relates to other studies which dealt with an analysis of the productivity and efficiency of the food processing sectors in Visegrád countries (among others: Cechura and Hockmann (2010 and 2011), Brasili et al. (2007), Bryla (2005)). The paper contributes to studies analyzing productivity and efficiency in the food processing industry, through an analysis of intercountry and inter- and intrasectoral heterogeneity in technology and efficiency in the food processing industry in Visegrád countries. In particular, the paper addresses two research questions. The first question is related to technology. We introduce a model specification which allows us to capture intercountry and inter- and intrasectoral heterogeneity in technology in one model specification. In other words, we complement the analysis of country- and sectoral-specific technology and firm heterogeneity. The second question concerns the significance of technical efficiency as well as the country and sectoral differences in technical efficiency. Technical efficiency, as an integral part of overall economic efficiency, is an important indicator of the competitiveness and productivity of companies. It provides information on the extent to which companies can increase the productivity of their inputs by catching up to the top-performing companies in a sector. Since the agri-food chain in Visegrád countries has experienced several important changes over the last decade, it is time to ask how the food processing sectors in Visegrád countries are performing.

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 model estimates and an analysis of intercountry and intersectoral heterogeneity in technology and technical efficiency in the chosen food processing industries. Chapter 5 contains a discussion and concluding remarks, including policy implications.

2 Theoretical considerations

2.1 Economic background

Since we are analysing a food processing industry which is dominated by large companies[1], often registered on the stock market, we follow Georgescu-Roegen (1951) and assume that companies maximise their return on capital (r), instead of conventional profits maximisation assumption. In the case of large companies, shareholders (or owners in general) are primarily interested in a high dividend from the exerted capital; profit maximisation can be considered of secondary importance. That is, maximizing returns on capital appears to be a more appropriate decision rule in the case of the manager-operated but shareholder-owned companies which prevail in food processing[2].

[1] This is especially true if we use the Amadeus dataset in the analysis.

[2] Our decision rule is a modification of the returns for a dollar model (Färe et al., 2002).

In terms of the transformation function, the technical production possibilities are given by $f(\mathbf{x}, k, \mathbf{y}^*) = 1$, where ***y**** and ***x*** denote vectors of (technically efficient) outputs and inputs, respectively, and k represents capital. The relation between technically efficient and actual output is given by $\mathbf{y}^* = \mathbf{y}e^u$, where $u \geq 0$ indicates inefficiency, i.e., the amount by which output can be increased without changing the bounds of the transformation function.

Denoting the prices for inputs and output by ***w*** and ***p*** and for capital by ***r*** the optimisation problem becomes:

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

After small mathematical manipulations, the first-order conditions are:

$$\frac{p_j\, y_j^*}{k} + \lambda\ f(\mathbf{x}, k, \mathbf{y}^*) \frac{\partial \ln f(\mathbf{x}, k, \mathbf{y}^*)}{\partial \ln y_j^*} = 0, \text{ for j = 1,...,J}$$

$$-\frac{w_i x_i}{k} + \lambda\ f(\mathbf{x}, k, \mathbf{y}^*) \frac{\partial \ln f(\mathbf{x}, k, \mathbf{y}^*)}{\partial \ln x_i} = 0, \text{ for i = 1,..,I} \qquad (2)$$

$$-\frac{\mathbf{p}'\mathbf{y}^* - \mathbf{w}'\mathbf{x}}{k} + \lambda\ f(\mathbf{x}, k, \mathbf{y}^*) \frac{\partial \ln f(\mathbf{x}, k, \mathbf{y}^*)}{\partial \ln k} = 0$$

where λ is the Lagrange multiplier from the maximization problem.

The first-order conditions in (2) imply:

$$\sum_j \frac{\partial \ln f(\mathbf{x}, k, \mathbf{y}^*)}{\partial \ln y_j^*} = -\sum_i \frac{\partial \ln f(\mathbf{x}, k, \mathbf{y}^*)}{\partial \ln x_i} - \frac{\partial \ln f(\mathbf{x}, k, \mathbf{y}^*)}{\partial \ln k}. \qquad (3)$$

The virtue of (3) is that it allows an investigation of input and output structures that comply with the conditions of economic optimisation using only information on quantities. Since price data are often scarcely available, assuming that returns on capital are maximized instead of profits provides an additional advantage for the empirical analysis.

Before the empirical implementation is presented, a further implication of maximising the returns on capital will be developed. Since the first-order conditions (2) imply:

$$\frac{\partial f}{\partial x_i} = -\frac{w_i}{p_j} \frac{\partial f}{\partial y_j^*} \quad \text{for all i and j}$$

$$\frac{\partial f}{\partial y_l^*} = \frac{p_l}{p_j} \frac{\partial f}{\partial y_j^*} \quad \text{for all l and l} \neq \text{j, and}$$

$$\frac{\partial f}{\partial k_l^*} = -\frac{r}{p_j} \frac{\partial f}{\partial y_j^*},$$

Condition (3) can be expressed as:

$$\mathbf{p}'\mathbf{y}^* = \mathbf{w}'\mathbf{x} + rk\,. \qquad (4)$$

Thus total revenues are distributed for the remuneration of inputs. The only condition under which (4) is fulfilled is that the processors operate at constant returns to scale. Thus, compared to pure profit maximization, the maximization of the returns on capital implies an additional restriction regarding the scale of production. Moreover, testing (4) provides information on whether the empirical observations are consistent with decision rule (1).

2.2 Empirical implementation

In the empirical analysis we assume that the transformation process can be well approximated by a translog transformation function. However, instead of a vector of outputs we have only one output *y*:

$$\begin{aligned} \ln f(\mathbf{x}, y^*, k) &= a_0 + \alpha_y \ln y^* + \frac{1}{2}\alpha_{yy} \ln y^{*2} \\ &+ \sum_i b_i \ln x_i + \frac{1}{2}\sum_i \sum_j \beta_{ij} \ln x_i \ln x_j + \ln y^* \sum_i \delta_{yi} \ln x_i \\ &+ \gamma_k \ln k + \frac{1}{2}\gamma_{kk} \ln k^2 + \ln k \sum_i \delta_{ik} \ln x_i + \delta_{yk} \ln k \ln y^* = 0 \end{aligned} \qquad (5)$$

In this case condition (3) becomes:

$$\begin{aligned} &\alpha_y + \alpha_{yy} \ln y^* + \sum_i \delta_{yi} \ln x_i + \delta_{yk} \ln k = \\ &-\left(\sum_i \beta_i + \gamma_k\right) - \sum_i \ln x_i \left(\sum_j \beta_{ij} + \delta_{ki}\right) - \ln y^* \left(\sum_i \delta_{yi} + \delta_{yk}\right) - \left(\sum_i \delta_{ki} + \gamma_{kk}\right) \ln k \end{aligned} \qquad (6)$$

In order to facilitate the empirical analysis, we assume that the technology can be expressed in the form of an input distance function. Since the input distance function is homogeneous of degree 1 in all inputs (***x***,*k*), the following restrictions apply to the transformation function:

$$\begin{aligned} &\sum_i b_i + \gamma_k = -1 \\ &\sum_j \beta_{ij} + \delta_{ik} = 0, \ \text{for } i = 1,\dots,I \\ &\sum_i \delta_{ki} + \gamma_{kk} = 0 \\ &\sum_i \delta_{yi} + \delta_{yk} = 0 \end{aligned} \qquad (7)$$

After applying these restrictions and normalising by ***k***, (6) reduces to:

$$\alpha_y + \alpha_{yy} \ln y^* + \sum_i \delta_{ki} \frac{\ln x_i}{\ln k} = -1, \qquad (8)$$

which holds for every x and y only when $\alpha_y = -1$, $\alpha_{yy} = 0$, and $\delta_{ki} = 0 \ \forall i$.

Using these restrictions, the transformation function gives:

$$\ln \frac{y^*}{k} = \alpha_0 + \sum_i \beta_i \ln \frac{x_i}{k} + \frac{1}{2} \sum_i \sum_j \beta_{ij} \ln \frac{x_i}{k} \ln \frac{x_j}{k}. \qquad (9)$$

Equation (model) (9) plays a central role in the empirical application.

2.3 *Efficiency, productivity and heterogeneity*

A) Efficiency

Given the definition of inefficiency (u) and adding a term (v) which accounts for random variation (statistical noise), the model estimated in the empirical analysis is given by:

$$\ln \frac{y}{k} = \alpha_0 + \sum_i \beta_i \ln \frac{x_i}{k} + \frac{1}{2} \sum_i \sum_j \beta_{ij} \ln \frac{x_i}{k} \ln \frac{x_j}{k} - u + v. \qquad (10)$$

Equation (10) can be estimated using standard stochastic frontier techniques. Besides requiring only quantity information and still complying with economic optimization, (10) has the further advantage that it could reduce the endogeneity problem involved in estimating distance functions (Kumbhakar, 2011). Since the endogeneity problem often frustrates estimation (Marschak and Andrews (1944), Olley and Pakes (1996), Levinsohn and Petrin (2003) and others) and can lead to an inconsistent parameter estimate, the derived function can be regarded as a possible way of avoiding the problem in the empirical application.

B) Productivity

Productivity finds its expression in the shape of (10), and thus the parameter vector (a_0, $\boldsymbol{\beta}$). 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 not only induce 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 this way and extend (10) by:

$$\alpha_0 = b_0 + b_t t + \frac{1}{2} \beta_{tt} t^2 \quad and \quad \alpha_j = b_j + \beta_{jt} t, \forall j. \qquad (11)$$

The resulting function

$$\ln \frac{y}{k} = b_0 + b_t t + \frac{1}{2} \beta_{tt} t^2 + \sum_{j \neq 1} b_j \ln \frac{x_j}{k} + \sum_{j \neq 1} \beta_{jt} t \ln \frac{x_j}{k} + \frac{1}{2} \sum_{j \neq 1} \sum_{k \neq 1} \beta_{jk} \ln \frac{x_j}{k} \ln \frac{x_k}{k} - u + v \qquad (12)$$

will be used as a benchmark in the empirical application.

Given the panel structure of the data we assume that the efficiency term $\boldsymbol{u}$ is allowed to vary among firms, unlike a random effect model (Pitt and Lee 1981). 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.

C) Heterogeneity

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. Moreover, we assume that there can be significant country-specific technology in some sectors. We consider these three kinds of heterogeneity by expanding the first-order terms in (12):[3]

$$\begin{aligned} b_0 &= \beta_0 + \sum_s d_s \beta_s + \beta_\eta \eta, \\ b_t &= \beta_t + \sum_s d_t \beta_{st} + \beta_{t\eta} \eta, \\ b_j &= \beta_j + \sum_s d_s \beta_{js} + \beta_{j\eta} \eta, \forall j \end{aligned} \tag{13}$$

In (13), d represents dummy variables which account for intersectoral and intercountry differences in technologies. In the empirical application, we distinguish between five sectors (slaughtering, dairy, milling, feedstuffs, and others) and five countries (Visegrád countries (Czech Republic, Hungary, Poland, Slovakia) and other EU countries). 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. In the estimation, we assume that η follows a standard normal distribution, i.e., $\eta \sim N(0,1)$. The specification given by (12) and (13) 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).

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

$$\ln \frac{y_{it}}{k_{it}} = g(\mathbf{x}^*_{it}, t, \mathbf{d}, \eta_i) - u_{it} + v_{it}, \text{ with}$$

$$v_{it} \sim N(0, \sigma_v^2),\ u_{it} \sim \mathrm{N}^+(0, \sigma_u^2) \text{ and } \eta_i \sim \mathrm{N}(0,1). \tag{14}$$

The function g(•) captures all influences discussed using (12) and (13). The vector **d** represents the sector and country dummies, and **x*** contains the transformed right-hand-side variables in (12). The subscripts i and t denote firm and time, respectively. Since we use the

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[3] The true effect model results from (13) by assuming that b_t and all b_j are constants and all β_{ss} are zero.

unbalanced panel dataset, $t \in \Im(i)$ and $\Im(i)$ represents a subset of years T_i from the whole set of years T ($1, 2, \ldots, T$), for which the observations of the *i-th* processing firm are in the data set.

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 $E[u| u + v]$.

3 Data set

The data we use in the analysis is drawn from the Amadeus database, created and produced by Bureau van Dijk. The database contains financial information for public and private companies across Europe. The database provides detailed information about (standardised) annual accounts, financial ratios, sectoral activities and ownership information. [4]

The panel data set that we use in our analysis contains companies whose main activity is food processing according to the NACE classification (NACE 10 – manufacture of food products – groups from 10.1 to 10.9). It is an unbalanced panel data set, which represents the period from 2003 to 2012 and contains 9,885 food processing companies from 27 EU countries. Since not all companies in the database have complete information, we exclude those companies with negative and zero values of the variables of interest. Thus, we were constrained to using an unbalanced panel data set containing 8,110 companies with 52,682 observations, i.e., on average 6.5 observations per company in the period from 2003 to 2012. Table 1 presents the structure of the data set.

Table 1. Structure of the Data Set

Country		Sector					Total
		Slaughtering	Dairy	Milling	Feedstuff	Others	
EU 27		12,533	6,486	3,326	4,845	25,492	52,682
CEFTA:	Czech Republic	385	283	110	234	875	1,887
	Hungary	228	79	61	90	348	806
	Poland	1,251	765	215	253	1,622	4,106
	Slovakia	93	87	36	111	178	505

Source: Amadeus database and our own calculations

The following variables were used in the analysis: output (y_{it}), labour (L_{it}), capital (C_{it}) and inputs (material) (M_{it}). Output represents operating revenue (Turnover) of the company. Labour input is total number of employees. Capital represents the book value of fixed assets. Finally, variable inputs (materials) were used in the form of total costs of materials and energy consumption per company. Output was deflated by the sectoral index of food processing prices (EU level – 27 countries; 2010 = 100) and capital, and inputs were deflated by the index of producer prices in industry (country level; 2010 = 100).

[4] More information on the Amadeus database is provided at: http://www.bvdinfo.com.

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 Heterogeneity in production structures

We first discuss the question of whether a model formulation as flexible as that provided in (14) is an appropriate choice for the analysis of Visegrád food processing. We alternated with a different model specification nested in the model formulation (14), and we tested whether the more flexible formulations contribute to the explanatory power of the model. In other words, we tested whether the heterogeneity in production structures is pronounced. 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 EU food processing. Thus we conclude that the model given by (14) is the most appropriate formulation.

Given the results of the likelihood ratio test, we will consider the parameter estimates of RPM with sector and country effects only (Table 4). The table is organised as follows: first, we present the first-order effects separated into intercountry, inter- and intrasectoral effects. Then, the second-order effects and characteristic of inefficiency are provided.

We start by discussing some general characteristics of the estimates. The estimated parameters conventionally discussed in production function estimates are highly significant. This also holds for the coefficients which capture inter- and intrasectoral heterogeneity. The intercountry heterogeneity is pronounced only for some sectors in Visegrád countries. Thus, we can already conclude that heterogeneity among firms as well as among sectors is an important characteristic in EU food processing, and has to be considered when conducting a reliable analysis of the sector. As far as the heterogeneity among Visegrád countries is concerned, we can conclude that some country-specific effects are pronounced. In other words, we found significant heterogeneity for some sectors in Visegrád countries.

The estimation results can furthermore be evaluated by checking whether the theoretical consistency of production technology is fulfilled. Specification (5) and the restrictions in (7) imply the estimation of an input distance function. Thus, even though we use a further restriction, the functional form in (9) should inherit the properties of an input distance function. Färe and Primont (1995) show that this representation of production technology should be non-increasing in outputs, as well as non-decreasing and concave in inputs. The monotonicity requirements for inputs results in $\beta_L > 0$, $\beta_V > 0$ and $\beta_L + \beta_V < 1$. Table 2 shows that these conditions are met, even if intersectoral and intercountry heterogeneity is considered. Diminishing marginal returns (concavity) in inputs requires $\beta_{qq} + \beta_q^2 - \beta_q < 0$ for q = L, V. This condition holds for all inputs[5]. The monotonicity requirement for output is also fulfilled, because restriction (8) was directly applied.

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

Table 2. Parameter estimates

Distance function								
First-order effects								
i = 1, …,4.	1 = Constant		2 = Time		3 = Labour		4 = Materials	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
βi	0.2078***	0.0014	0.0130***	0.0004	0.1392***	0.0008	0.7446***	0.0007
$\beta i_{\_slaughter}$	-0.0817***	0.0019	0.0010	0.0007	0.0760***	0.0014	-0.0858***	0.0009
$\beta i_{\_dairy}$	-0.0494***	0.0024	0.0020	0.0012	0.0272***	0.0021	0.0220***	0.0017
$\beta i_{\_milling}$	-0.0233***	0.0033	-0.0234***	0.0015	0.0192***	0.0021	-0.0893***	0.0017
$\beta i_{\_feedstuffs}$	0.1258***	0.0024	-0.0217***	0.0011	0.1884***	0.0017	-0.1770***	0.0013
$\beta i,_{CZ\_slaughter}$	-0.0170	0.0151	-0.0057	0.0046	-0.0133	0.0127	0.0069	0.0110
$\beta i,_{CZ\_dairy}$	-0.0102	0.0143	0.0101**	0.0042	-0.0140	0.0109	-0.0044	0.0139
$\beta i,_{CZ\_milling}$	-0.0040	0.0215	-0.0030	0.0084	-0.0030	0.0208	0.0025	0.0229
$\beta i,_{CZ\_feedstuffs}$	-0.0072	0.0112	0.0042	0.0052	-0.0247*	0.0130	0.0026	0.0097
$\beta i,_{HU\_slaughter}$	-0.0162	0.0155	-0.0288***	0.0060	-0.0301***	0.0097	-0.0017	0.0070
$\beta i,_{HU\_dairy}$	0.0030	0.0420	-0.0266**	0.0126	0.0053	0.0318	-0.0240**	0.0116
$\beta i,_{HU\_milling}$	-0.0028	0.0383	-0.0019	0.0180	0.0008	0.0236	0.0024	0.0238
$\beta i,_{HU\_feedstuffs}$	-0.0050	0.0213	0.0055	0.0109	0.0014	0.0117	-0.0100	0.0117
$\beta i,_{PL\_slaughter}$	-0.0684***	0.0075	-0.0001	0.0025	-0.0301***	0.0055	0.0344***	0.0046
$\beta i,_{PL\_dairy}$	-0.0295***	0.0092	-0.0056*	0.0031	-0.0192**	0.0088	-0.0216***	0.0051
$\beta i,_{PL\_milling}$	-0.0184	0.0128	0.0034	0.0052	-0.0037	0.0136	0.0085	0.1249
$\beta i,_{PL\_feedstuffs}$	-0.0052	0.0128	0.0014	0.0046	-0.0077	0.0133	-0.0017	0.0131
$\beta i,_{SK\_slaughter}$	-0.0146	0.0227	-0.0160**	0.0081	-0.0283**	0.0135	0.0692***	0.0053
$\beta i,_{SK\_dairy}$	-0.0036	0.0258	0.0009	0.0107	0.0012	0.0286	-0.0045	0.0198
$\beta i,_{SK\_milling}$	-0.0022	0.0460	-0.0050	0.0201	0.0005	0.0408	0.0012	0.0753
$\beta i,_{SK\_feedstuffs}$	-0.0032	0.0286	-0.0060	0.0168	-0.0008	0.0684	0.0034	0.0284
$\beta_{0\eta}$	0.2718***	0.0007	0.0005*	0.0003	0.0925***	0.0004	0.1699***	0.0003

Second-order effects			
	Coef.	SE	Z-val.
β_{TT}	-0.0600	0.0003	0.0000
β_{AT}	0.0047	0.0002	0.0000
β_{VT}	0.0043	0.0001	0.0000
β_{AA}	0.0659	0.0004	0.0000
β_{VV}	0.0896	0.0002	0.0000
β_{AV}	0.0818	0.0002	0.0000
Sigma	0.2890	0.0001	0.0000
Lambda	2.5482	0.0060	0.0000

Note: ***, **, * denote significance at the 1%, 5% and 10% level.
Source: own calculations

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. However, significant differences in both sector and firm were revealed by the estimates. Moreover, we found significant country specifics in technology for materials in the Hungarian dairy sector, Polish slaughtering and dairy sectors, and Slovak slaughtering sector. For labour inputs the differences in technology were pronounced in the Czech feedstuff sector, Hungarian slaughtering sector, Polish slaughtering and dairy sectors, and Slovak slaughtering sector. Whereas in the case of materials the corresponding expenditure is lower in the selected industries, except for dairy, the cost share of labour is generally higher. Intersectoral effects were present for both inputs. However, their influences were much more pronounced for material inputs than for labour. One reason for this result is the price stability of the labour and material inputs. Conditions on the labour market are determined to a large extent by the macroeconomic environment, and the input prices (salaries) are not subject to high volatility, unlike the raw materials markets. On the raw materials markets, prices are usually defined in bilateral negotiations between farmers and processors and are characterised by high volatility over time.

As far as the country specifics in technology are concerned, the cost shares of labour are generally lower. The cost shares of materials are lower in the case of the Hungarian and Polish dairy sectors, and higher for Polish and Slovak slaughtering. Assuming that companies in food processing sectors have the same input prices (salaries), the technology in Czech feedstuffs, Hungarian, Polish and Slovak slaughtering and the Polish dairy sector is characterized by lower labour intensity compared to the EU average. On the other hand, since Polish and Slovak slaughtering have higher material cost shares, this suggests at the same time that the technology could be characterised by processing less processed products. In general, the differences in the Polish slaughtering and dairy sectors were pronounced for almost all first-order parameters.

In addition, we found that technical change did not have a strong impact. On average in the EU, production possibilities increased by 1.3% per year. However, technical change slightly decelerated in the period under investigation. Significant sector-specific effects were estimated for the milling and feedstuff industries. In these sectors, we estimated technological digression. Firm-specific effects were only slightly pronounced. Country-specific effects were pronounced in the Czech dairy sector, Hungarian slaughtering and dairy sectors, Polish dairy sector and Slovak slaughtering sector. The estimated effect was negative in all cases, except for the Czech dairy sector. The low or negative technological progress could be a result of the economic problems after 2008. In addition, the estimates for biased technical change are significant for both labour and material inputs, but are rather small. This suggests that technical change was predominately Hicks neutral.

4.2 Heterogeneity in Efficiency

The preceding discussion captures the inter- and intra-industry differences and country specifics that occur on the production frontier, namely that firms fully exploit their production possibilities. However, due to stochastic and systematic effects, output may be below the upper limit. The various reasons for inefficiency are not presented here[6]. We will deal instead with other related questions: (1) Are there pronounced efficiency differences among sectors and countries? (2) How did the intra-industry level of efficiency develop over time in

[6] See, e.g., Latruffe et al. 2004; Bokusheva, Hockmann 2006

Visegrád countries? In particular, do we observe falling-behind or catching-up processes within industries?

Table 3. TE in Slaughtering

Slaughtering		2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
EU - 27											
Minimum		0.2	0.27	0.14	0.14	0.32	0.14	0.23	0.25	0.14	0.69
Percentile:	10th	0.78	0.78	0.79	0.8	0.8	0.79	0.78	0.8	0.8	0.82
	Median	0.86	0.85	0.85	0.84	0.85	0.84	0.84	0.86	0.86	0.87
	90th	0.9	0.88	0.88	0.89	0.88	0.88	0.87	0.89	0.9	0.9
Maximum		0.97	0.98	0.96	0.97	0.98	0.98	0.98	0.98	0.98	0.93
Germany											
Minimum		0.83	0.83	0.78	0.79	0.77	0.77	0.8	0.8	0.82	0.84
Percentile:	10th	0.84	0.84	0.83	0.8	0.82	0.81	0.82	0.83	0.84	0.84
	Median	0.87	0.85	0.85	0.84	0.86	0.85	0.85	0.87	0.86	0.85
	90th	0.91	0.87	0.88	0.88	0.87	0.87	0.88	0.89	0.89	0.87
Maximum		0.92	0.88	0.91	0.89	0.88	0.89	0.9	0.9	0.91	0.89
Czech Republic											
Minimum		0.62	0.69	0.72	0.75	0.74	0.75	0.73	0.64	0.7	-
Percentile:	10th	0.77	0.74	0.76	0.77	0.81	0.78	0.77	0.81	0.75	-
	Median	0.86	0.83	0.82	0.84	0.85	0.84	0.84	0.86	0.84	-
	90th	0.9	0.89	0.88	0.88	0.89	0.88	0.88	0.9	0.9	-
Maximum		0.92	0.91	0.9	0.95	0.93	0.91	0.92	0.92	0.94	-
Hungary											
Minimum		-	0.65	0.65	0.63	0.56	0.65	0.66	0.75	0.14	-
Percentile:	10th	-	0.79	0.74	0.64	0.65	0.7	0.75	0.82	0.74	-
	Median	-	0.79	0.85	0.79	0.82	0.82	0.84	0.86	0.85	-
	90th	-	0.86	0.88	0.94	0.89	0.92	0.89	0.9	0.9	-
Maximum		-	0.86	0.89	0.94	0.9	0.98	0.95	0.97	0.94	-
Poland											
Minimum		0.56	0.69	0.69	0.63	0.42	0.59	0.48	0.56	0.48	0.69
Percentile:	10th	0.73	0.77	0.77	0.8	0.81	0.78	0.77	0.81	0.76	0.77
	Median	0.83	0.84	0.85	0.84	0.85	0.83	0.84	0.86	0.84	0.87
	90th	0.89	0.88	0.88	0.88	0.89	0.87	0.88	0.89	0.89	0.9
Maximum		0.93	0.97	0.92	0.93	0.93	0.93	0.98	0.95	0.95	0.91
Slovakia											
Minimum		0.8	0.8	0.76	0.73	0.66	0.14	0.64	0.65	0.66	0.14
Percentile:	10th	0.83	0.82	0.79	0.75	0.71	0.76	0.78	0.79	0.82	0.76
	Median	0.88	0.85	0.83	0.84	0.83	0.83	0.84	0.86	0.86	0.84
	90th	0.9	0.88	0.89	0.87	0.88	0.86	0.88	0.89	0.9	0.86
Maximum		0.91	0.88	0.89	0.87	0.96	0.86	0.88	0.91	0.92	0.96

Source: own calculations

Table 4: TE in Dairy

Dairy		2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
EU - 27											
Minimum		0.51	0.32	0.23	0.14	0.42	0.22	0.36	0.36	0.23	0.71
Percentile:	10th	0.77	0.78	0.83	0.83	0.83	0.78	0.8	0.8	0.81	0.83
	Median	0.84	0.84	0.86	0.87	0.87	0.83	0.85	0.85	0.86	0.87
	90th	0.88	0.88	0.88	0.9	0.9	0.87	0.89	0.88	0.89	0.9
Maximum		0.97	0.97	0.98	0.98	0.98	0.98	0.97	0.97	0.98	0.95
Germany											
Minimum		0,73	0.8	0.75	0.62	0.69	0.7	0.62	0.79	0.75	0.87
Percentile:	10th	0.79	0.8	0.79	0.84	0.81	0.8	0.83	0.83	0.83	0.88
	Median	0.85	0.84	0.85	0.87	0.84	0.83	0.86	0.86	0.86	0.9
	90th	0.9	0.88	0.88	0.89	0.86	0.86	0.88	0.88	0.88	0.93
Maximum		0.9	0.9	0.89	0.91	0.88	0.88	0.92	0.91	0.95	0.95
Czech Republic											
Minimum		0.64	0.57	0.68	0.76	0.64	0.72	0.72	0.65	0.71	-
Percentile:	10th	0.71	0.71	0.73	0.81	0.76	0.73	0.78	0.74	0.76	-
	Median	0.85	0.85	0.83	0.88	0.85	0.82	0.84	0.83	0.84	-
	90th	0.89	0.89	0.88	0.9	0.9	0.88	0.89	0.9	0.9	-
Maximum		0.91	0.94	0.89	0.95	0.93	0.92	0.93	0.96	0.94	-
Hungary											
Minimum		-	-	0.8	0.82	0.72	0.74	0.66	0.44	0.47	-
Percentile:	10th	-	-	0.8	0.88	0.77	0.75	0.74	0.76	0.57	-
	Median	-	-	0.85	0.93	0.81	0.82	0.87	0.83	0.86	-
	90th	-	-	0.9	0.95	0.87	0.87	0.9	0.89	0.89	-
Maximum		-	-	0.9	0.96	0.93	0.92	0.92	0.9	0.93	-
Poland											
Minimum		0.51	0.61	0.72	0.71	0.69	0.56	0.62	0.6	0.77	0.69
Percentile:	10th	0.76	0.81	0.83	0.83	0.81	0.74	0.8	0.79	0.82	0.75
	Median	0.82	0.84	0.86	0.86	0.87	0.81	0.85	0.86	0.86	0.86
	90th	0.87	0.88	0.89	0.89	0.89	0.86	0.88	0.88	0.89	0.9
Maximum		0.97	0.92	0.98	0.98	0.93	0.97	0.92	0.92	0.91	0.9
Slovakia											
Minimum		0.78	0.73	0.79	0.81	0.77	0.59	0.63	0.58	0.86	0.59
Percentile:	10th	0.79	0.75	0.8	0.82	0.8	0.68	0.76	0.67	0.87	0.77
	Median	0.84	0.84	0.86	0.87	0.85	0.82	0.86	0.82	0.88	0.85
	90th	0.89	0.9	0.94	0.89	0.89	0.85	0.88	0.9	0.97	0.89
Maximum		0.91	0.91	0.96	0.9	0.89	0.87	0.88	0.91	0.97	0.97

Source: own calculations

The answers to the questions are given in Tables 3 and 4. Due to limited space we present only the results for the slaughtering and dairy sectors, in which country-specific technology was most pronounced. The tables show that some features are common for all countries and both sectors. First, in each sector and country 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 median of technical efficiencies in Slaughtering (EU-27: 0.852; Czech Republic: 0.842; Hungary: 0.828; Poland: 0.845; Slovakia: 0.846) and Dairy sector (EU 27: 0.854; Czech Republic: 0.843; Hungary: 0.853; Poland: 0.849; Slovakia: 0.849) among countries, we can conclude that, on average, companies greatly exploit their production possibilities. Moreover, the median of technical efficiency do not significantly differ among Visegrád countries in both sectors. The same holds for the comparison of Visegrád countries with European average (EU-27). One exception is Hungarian slaughtering in which the median of technical efficiency is slightly lower compared to other Visegrád countries. On the other hand, the developments in the first deciles of technical efficiency differ among the countries in both sectors, and suggest that structural change will have a different power and speed in Visegrád countries in slaughtering and dairy sectors. 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 food processing companies.

Moreover, since the median of technical efficiency is high and close to the last deciles of 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 first decile of technical efficiency is subject of permanent changes. This suggests that some companies are falling behind. They may not be able to keep pace with competitors.

5 Conclusion

In this section we will concentrate on the questions raised in the introduction, namely the one regarding heterogeneity in production structures, as well as the second question concerning the significance of technical efficiency.

The analysis revealed significant differences in both sector and firm technologies. Moreover, we estimated significant country specifics in technology. This especially concerns Czech, Hungarian and Polish dairy sector, Czech feedstuff sector, Polish, Hungarian and Slovak slaughtering sector. Thus, the intercountry, intersectoral as well as heterogeneity among firms is an important characteristics in EU food processing.

As far as the technical efficiency is concerned, we can conclude that on average the food processing companies highly exploit their production capacities. In each analysed sector and Visegrád country the difference between best and average company is not large and is constant over time. This suggests that these food processing companies can keep space with competitors. On the other hand, the worst 10 % of companies are subject of permanent changes and some of them are falling behind.

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