Technological change in the Czech food processing industry: What did we experience in the last decade?

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Annotation: The paper examines the contribution of technological change to changes in technical efficiency and TFP (Total Factor Productivity). The results show that the technological change did not contribute significantly to the development of efficiency in all analyzed sector. However, the distribution of technical change suggests that the gap between the best and worst food processing companies increased within the analyzed period. On the other hand, the technological change was an important factor determining the TFP increase in all sectors.

Key terms: Technological change, Technical efficiency, TFP, Czech food processing industry

1 Introduction

What did we experience in the last decade? The Czech food processing industry went through significant institutional and economic changes. Accession to the European Union and the accompanying implementation of CAP principles called for the modernisation and enlargement of some processing capacities. Food processing companies had to modernize their production due to the acquisition of acquis communautaire in advance of the EU enlargement. The new standards forced financially poor companies to drop out of the market (Putićová, Mezera, 2008). Since the EU enlargement, processing companies have been operating on the common market. Tariffs and other barriers were removed either before or upon the entrance of the Czech Republic into the EU, which resulted in a significant increase in both the export, and especially the import, of food products (Šafaříková, Pohlová, 2008; Svatoš, Smutka, 2009). Export and import quantities became a significant determinant of production. The increasing trend in imports exceeded that of exports in the slaughtering, fruit and vegetable processing, and milling industries, and this resulted in a drop in production in these sectors. The figures and results of previous studies (Čechura and Hockmann, 2010 and 2011) suggest that some companies have problems with a competitive environment, and instead of taking advantage of opportunities in the common market, they are falling behind. Moreover, the high intrasectoral heterogeneity suggests that further adjustment processes will occur, and some Czech food processing industries will reduce their size (Čechura, Hockmann, 2011).

Since technological change is an important factor in a firm's competitiveness, we examine its contribution to changes in TFP (Total Factor Productivity) as well as its determinants. In particular, the following questions will be explored. The first question relates to technical change and technical efficiency. The aim is to identify which food processing industries are following a path of sustainable development, characterized by the adoption of innovation and reduced waste of resources due to inefficient input use, and to identify the factors which determine developments in the analyzed industries. The second question concerns the contribution of technological change to productivity development. The aim is to assess the extent to which technological change contributed to changes in TFP. The last question concerns sector-specific development. The aim is to assess the inter- and intra-sectoral specifics of technology, efficiency and TFP development.

2 Data and Methodology

The questions will be explored by estimating a joint stochastic frontier production function model for the Czech food processing industry. The estimation of a stochastic frontier production function model for the Czech food processing industry follows Čechura (2009). Čechura (2009) showed that the presence of significant heterogeneity in firms overestimates technical inefficiency. Considering both the theoretical criteria of the production function and significant heterogeneity of firms, the author suggests using the Fixed Management model. This paper will use the same data set, and therefore the Fixed Management model is considered to be a proper choice.

The analysis is based on the assumption that production possibilities can be approximated by a frontier production function which has the translog form. Following Álvarez et al. (2003 and 2004), the Fixed Management model in a translog form is specified as follows:

$$\ln TE_{it} = \ln f(t, \mathbf{x}_{it}, m_i; \boldsymbol{\beta}) - \ln f(t, \mathbf{x}_{it}, m_i^*; \boldsymbol{\beta}) \leq 0 \quad , \quad \ln TE_{it} = -u_{it} \quad , \tag{1}$$

and

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

where $\mathbf{x}_{it}$ is a vector of inputs containing $K=3$ production factors - Labour (A_{it}), Capital (C_{it}) and Material (M_{it}). Indices i, where $i = 1, 2, \ldots, N$, and t, where $t \in \Im(i)$, refer to a particular food processing company and time, respectively, 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* food processing company are in the data set. α is an intercept (productivity parameter). $\boldsymbol{\beta}$ are parameters to be estimated that determine the production function f. Technical efficiency, $TE_{i(t)}$, with $0 \leq TE_{i(t)} \leq 1$, captures deviations from the maximum achievable output. v_{it} captures statistical noise in the data and $u_{i(t)}$ is the inefficiency term. The random error (statistical noise) v_{it} and technical inefficiency term $u_{i(t)}$ of the stochastic frontier production function model are assumed to be $v_{it} \sim iid\ N(0, \sigma_v^2)$, $u_{i(t)} \sim iid\ N^+(0, \sigma_u^2)$ and to be distributed independently of each other, and of the regressors (for further references see Kumbhakar and Lovell, 2000). $m_i^* \sim \bullet(0,1)$ represents unobservable fixed management. The symbol $\bullet$ expresses that m_i^* could possess any distribution with zero mean and unit variance (Hockmann and Pieniadz, 2008). The difference between real (m_i) and optimal (m_i^*) management determines the level of technical efficiency /see relation (1)/. Technical efficiency is defined by:

$$\ln TE_{it} = \gamma_0 + \gamma_t t + \boldsymbol{\gamma}_{\mathbf{x}}' \ln \mathbf{x}_{it} \quad , \tag{3}$$

where

$$\gamma_0 = \beta_m (m_i - m_i^*) + \frac{1}{2}\beta_{mm}(m_i^2 - m_i^{*2})$$

$$\gamma_t = \beta_{tm}\left(m_i - m_i^*\right)$$

$$\boldsymbol{\gamma}_{\mathbf{x}} = \boldsymbol{\beta}_{xm}\left(m_i - m_i^*\right)$$

The technical efficiency consists of three components:

(i) time-invariant, firm-specific effect – management – γ_0,

(ii) interaction of m^* with time – technological change – γ_t,

(iii) interaction of m^* with the inputs quantity and quality – scale effect – $\boldsymbol{\gamma}_{\mathbf{x}}$.

Álvarez et al. (2004) showed that u_{it} can be estimated, according to Jondrow et al. (1982), as (4) with simulated m_i^* according to relation (5).

$$E\left[u_{it}\middle|\varepsilon_{it}, m_i^*\right] = \frac{\sigma\lambda}{\left(1+\lambda^2\right)}\left[\frac{\phi\left(-\left(\varepsilon_{it}\middle|m_i^*\right)\lambda/\sigma\right)}{\Phi\left(-\left(\varepsilon_{it}\middle|m_i^*\right)\lambda/\sigma\right)} - \frac{\left(\varepsilon_{it}\middle|m_i^*\right)\lambda}{\sigma}\right], \qquad (4)$$

where $\lambda = \dfrac{\sigma_u}{\sigma_v}$, $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\varepsilon_{it} = v_{it} - u_{it}$.

$$\hat{E}\left[m_i^*\middle|\mathbf{y}_i, \mathbf{X}_i, \boldsymbol{\delta}\right] = \frac{\frac{1}{R}\sum_{r=1}^{R} m_{i,r}^*\, \hat{f}\left(\mathbf{y}_i\middle|t, m_{i,r}^*, \mathbf{X}_i, \boldsymbol{\delta}\right)}{\frac{1}{R}\sum_{r=1}^{R} \hat{f}\left(\mathbf{y}_i\middle|t, m_i^*, \mathbf{X}_i, \boldsymbol{\delta}\right)} \qquad (5)$$

The Fixed Management model is fitted with a maximum simulated likelihood using NLOGIT version 4.0 - LIMDEP version 9.0 (Green, 2007). In the model, 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.

Total factor productivity is calculated in the form of the Törnqvist-Theil index (TTI) (see, e.g., Čechura, Hockmann, 2010). The Törnqvist-Theil index exactly determines the changes in production resulting from input adjustments having a production function in the translog form (for the proof see Diewert, 1976). Furthermore, Caves et al. (1982) showed the TTI extension for multilateral consistent comparisons.

Changes in TFP can be expressed (Čechura, Hockmann, 2010) as either a ratio (on the mean) of the output and input index (for CRS), or a multiplication of TFP components, i.e., scale effect (SE), technical efficiency effect (TE), technological change effect (TCH) and management effect (MAN).

$$\ln TFP_{it} = \ln\psi_{it} - \ln\iota_{it}^{CRS} = \underset{SE}{\ln\iota_{it}} + \underset{TE}{\ln\upsilon_{it}} + \underset{TCH}{\ln\tau_{it}} + \underset{MAN}{\ln\mu_{it}}, \qquad (6)$$

where[1]

$$\ln\psi_{it} = \ln y_{it} - \overline{\ln y_{it}}, \qquad (7)$$

[1] A bar over a variable specifies the arithmetic mean over all observations. If no aggregation is needed, i.e., only the development of one variable is depicted, the index simplifies into the deviation from the mean of the variables.

$$\ln \iota_{it}^{CRS} = \frac{1}{2}\sum_{j=1}^{K}\left[\left(\frac{\varepsilon_{it,j_0}}{\sum_{i=1}^{K}\varepsilon_{it,j_0}} + \frac{\bar{\varepsilon}_j}{\sum_{i=1}^{K}\varepsilon_{j_0}}\right)\left(\ln x_{it,j} - \overline{\ln x_j}\right) + \frac{\bar{\varepsilon}_j}{\sum_{i=1}^{K}\varepsilon_{j_0}}\overline{\ln x_j} - \overline{\frac{\varepsilon_{it,j_0}}{\sum_{i=1}^{K}\varepsilon_{it,j_0}}\ln x_{it,j}}\right], \quad (8)$$

$$\ln \iota_{it}^{VRS} = \frac{1}{2}\sum_{j=1}^{K}\left[\left(\varepsilon_{it,j_0} + \bar{\varepsilon}_j\right)\left(\ln x_{it,j} - \overline{\ln x_j}\right) + \bar{\varepsilon}_j\,\overline{\ln x_j} - \overline{\varepsilon_{it,j_0}\ln x_{it,j}}\right],$$
$$\text{with} \quad \varepsilon_{it,j_0} = \frac{\partial \ln f\left(t, x_{it,j};\boldsymbol{\beta}\right)}{\partial \ln \mathbf{x}_{it,j}} \quad (9)$$

$$\ln \iota_{it} = \ln \iota_{it}^{VRS} - \ln \iota_{it}^{CRS} \quad , \quad (10)$$

$$\ln \upsilon_{it} = \ln TE_{it} - \overline{\ln TE_{it}} \ , \quad (11)$$

$$\ln \tau_{it} = \frac{1}{2}\left[\left(\varepsilon_t + \bar{\varepsilon}_t\right)\left(t - \bar{t}\right) + \bar{\varepsilon}_t\bar{t} - \overline{\varepsilon_t t}\right], \quad with \quad \varepsilon_t = \frac{\partial \ln f\left(x_{it,j}, t, m_i\right)}{\partial t} \ , \quad (12)$$

$$\ln \mu_{it} = \frac{1}{2}\left[\left(\varepsilon_{m_0} + \bar{\varepsilon}_m\right)\left(m_i - \overline{m}_i\right) + \bar{\varepsilon}_m\overline{m}_i - \overline{\varepsilon_m m_i}\right], \quad with \quad \varepsilon_m = \frac{\partial \ln f\left(x_{it,j}, t, m_i\right)}{\partial m_i} \ . \quad (13)$$

Data set

The panel data set is drawn from the database of the Creditinfo Monitor of Companies, collected by Creditinfo Czech Republic, s.r.o. The database contains all registered companies and organisations in the Czech Republic. The analysis uses information from the final accounts of companies whose main activity is food processing in the period from 2000 till 2007. After the cleaning process (removing outliers and negative values of the variable of interest), the unbalanced panel data set contains 1,375 food processing companies with 6,473 observations, covering the period from 1998 to 2007.

The following variables, as defined above, are used in the analysis: Output, Labour, Capital and Material. Output is represented by the total sales of goods, products and services of the food processing company. Output was deflated by the index of food processing prices (2005=100). The Labour input is total personnel costs per company, divided by the average annual regional wage in the food processing industry (region = NUTS 3). Capital 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).

3 Results and Discussion

3.1 Parameter estimates

Table 1: Parameter estimates

Fixed Management model							
Variable	Coefficient	Std. Error	P[│Z│>z]	Variable	Coefficient	Std. Error	P[│Z│>z]
Means for random parameters				TT	0.00887	0.00102	0.0000
Constant	-0.05543	0.00349	0.0000	AT	0.01360	0.00136	0.0000
A	0.28800	0.00343	0.0000	CT	-0.00498	0.00079	0.0000
C	0.04557	0.00217	0.0000	MT	-0.00130	0.00094	0.1684
M	0.66928	0.00236	0.0000	AA	0.15032	0.00475	0.0000
T	0.02208	0.00108	0.0000	CC	0.02304	0.00135	0.0000
Coefficient on unobservable fixed management				MM	0.16616	0.00214	0.0000
Beta_m	0.13439	0.0021	0.0000	AC	-0.00171	0.00187	0.3624
A	0.06573	0.00257	0.0000	AM	-0.13543	0.00314	0.0000
C	0.05000	0.00142	0.0000	CM	-0.01886	0.00113	0.0000
M	-0.18721	0.00205	0.0000				
T	0.00054	0.00110	0.6204				
Beta_mm	-0.18987	0.00283	0.0000				
Log likelihood function	845.0026			Lambda	7.85261	0.44175	0.0000
No. of parameters	23			Sigma	0.25356	0.00108	0.0000
Sigma v	0.03203			Sigma u	0.25152		

Source: own calculations

Table 1 provides the results of parameter estimates. The estimated production elasticities imply theoretical consistency of the estimates. That is, the elasticities are positive (monotonicity), and diminishing marginal productivity (quasi-concavity) for each input was estimated ($\beta_{rr} + \beta_r^2 - \beta_r < 0$, for *r = A, C* and *M).*

Production elasticities were also found to be robust under different model specifications (see Čechura, 2009). Material has the highest impact on production, with production elasticities (β_M) 0.66928, which is also consistent with empirical observations. Labour elasticity (β_A) is 0.2880, which corresponds to the ratio of personnel costs to total output. The production elasticity of Capital is 0.04557, which is a lower intensity than we would expect. This could be caused by two factors working together. First, the accounting data does not contain information about leasing, which is an important source of capital in the Czech Republic. Second, a food processing company can face capital market imperfections.

Technical change has a strong positive impact on production, and it accelerates over time. On average, the production possibilities increased by 2.2% per year. The hypothesis that the parameters are time-invariant (H_0: $\beta_T=\beta_{TT}=\beta_{AT}=\beta_{LT}=\beta_{CT}=\beta_{MT}=0$) [2], as well as the null hypothesis about the Hicks neutral technological change (H_0: $\beta_{AT}=\beta_{LT}=\beta_{CT}=\beta_{MT}=0$)[3], was

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[2] LR test: FM model (LR = 291.2976); $\chi^2_{1-0.05}(5) = 11.070$.

[3] LR test: FM model (LR = 86.5034); $\chi^2_{1-0.05}(3) = 7.815$.

rejected at a 5% level of significance. The technological progress was characterized as Labour-using, and Capital- and Material-saving.

The parameter lambda is significant at a 5% significance level, and its value implies that variation in the u_{it} is more pronounced than variation in the random component v_{it}. This suggests that efficiency differences among firms are an important reason for variations in production.

The monotonicity requirements on management imply that the first derivatives of the production function with respect to management, $\frac{\partial y_{it}}{\partial m_i} > 0$, are positive for all companies. Verification of this requirement using the level of actual management, m_i, calculated from relation (3), shows consistency with theoretical requirements, i.e., an increase in management implies an increase in production for all companies.

Coefficients of unobservable fixed management (β_m ,β_{mm} ,β_{Am} ,β_{Cm} ,β_{Mm}) are statistically different from zero, even at a 1% significance level, which is evidence of correctly choosing the Random Parameter model as opposed to the conventional stochastic frontier approach. The insignificance of Technological Change implies that Technological Change did not contribute to the change in management productivity in the analyzed period ($\beta_{Tm} = 0$). Moreover, the positive sign on management $\beta_m > 0$ and negative on squared management $\beta_{mm} < 0$ implies that management determines production positively (see monotonicity) but with decreasing effect. Finally, an increase in management causes an increase in production elasticity and the marginal productivity of Material ($\beta_{Mm} < 0$), and a decrease in production elasticity and the marginal productivity of Labour and Capital ($\beta_{Am} > 0, \beta_{Cm} > 0$).

In terms of technical efficiency (Álvarez et al., 2004), the change in technical efficiency resulting from a change in management and inputs is given by:

$$\frac{\partial \ln TE_{it}}{\partial m_i} = \beta_m + \beta_{mm} m_i + \beta_{tm} \mathbf{t} + \boldsymbol{\beta}_{xm} \mathbf{lnx}_{it} \quad ,$$

$$\frac{\partial \ln TE_{it}}{\partial \mathbf{lnx}_{it}} = \boldsymbol{\beta}_{xm} \left(m_i - m_i^*\right) \quad \text{and} \quad \frac{\partial \ln TE_{it}}{\partial t} = \beta_{tm} \left(m_i - m_i^*\right) . \tag{13}$$

Relation (13), together with $\beta_m > 0$ and $\beta_{mm} < 0$, implies that an increase in m_i has a positive but decreasing effect on technical efficiency. An increase in Material implies a higher technical efficiency for a given level of management. Labour and Capital have an opposite effect.

Table 2 provides production elasticities with optimal and actual management calculated on the mean of the sample. The production elasticities with optimal management (m_i*), i.e., on the production frontier, are very close to the means of the random parameters. This is especially due to the fact that coefficients of unobservable fixed management (β_{rm}, for $r = A, C, M$) are very low compared to the means of random parameters. Since the mean of actual management is different from the mean of optimal management, the production elasticities calculated with actual management differ significantly compared to means of random parameters.

Table 2: Production elasticities with optimal and actual management

	Production elasticities with m_i*	Production elasticities with m_i
A	0.28889	0.23230
C	0.04343	0.00038
M	0.67157	0.83276
RTS (Returns to Scale)	1.00388	1.06544

Source: own calculations

The sum of production elasticities with optimal management is equal to 1.00388, and with actual management to 1.06544. That is, for the average company in the full sample, there is no indication of economies of scale for optimal management. However, if actual management is considered, there is an indication of increasing returns to scale.

Table 3 presents information about the production elasticities in selected branches of the food processing industry. The results suggest that there is no indication of economies of scale in the selected branches on the sample mean, except for the beverages industry. However, Table 4 shows that the differences among companies are large in all branches.

Table 3: Production elasticities (with m_i*) and Returns to Scale[4]

	A	C	M	RTS	Cases
Slaughtering	0.21255	0.03667	0.76545	1.01467	465
Dairy	0.20685	0.04891	0.75093	1.00668	252
Milling	0.21611	0.03286	0.75948	1.00846	134
Feedstuffs	0.22691	0.04495	0.73785	1.00970	222
Beverages	0.35725	0.07027	0.54493	0.97244	354

Source: own calculations

Table 4: Descriptive statistics of Returns to Scale

	Mean	Std.Dev.	Minimum	Maximum	Cases
Food processing industry	1.00388	0.06225	0.68607	1.20800	2298
Slaughtering	1.01467	0.04014	0.77930	1.13119	465
Dairy	1.00669	0.06043	0.78168	1.10678	252
Milling	1.00846	0.04570	0.86151	1.10771	134
Feedstuffs	1.00970	0.04559	0.85445	1.08468	222
Beverages	0.97244	0.07694	0.74594	1.20800	354

Source: own calculations

Finally, if management is considered to be a production factor, there is a dramatic change in economies of scale. The direct effect of management is given by:

$$\frac{\partial \ln y_{it}^{(*)}}{\partial m_i^*} = \beta_m + \beta_{mm} m_i^{(*)} + \beta_{tm} \mathbf{t} + \boldsymbol{\beta}_{xm} \mathbf{lnx}_{it} \quad . \qquad (14)$$

For the average company in the full sample, the direct effect of management is 0.1489 for optimal management and 0.3123 for actual management. This suggests that if management enters the production function as a production factor, the food processing company has increasing returns to scale. However, the interpretation of marginal values of management is difficult, since management does not have explicitly defined units. On the other hand, the results suggest that management could be considered an important determinant of food processing production.

[4] The calculations are carried out on the sample mean of the given branch.

3.2 Technical efficiency development

The development of technical efficiency and its components for the food processing industry and its selected individual branches is shown in Figure 1. Technical efficiency in the food processing industry did not change significantly within the period from 2000 to 2007. The rather volatile development of technical efficiency at the beginning of the analyzed period can be attributed to the low number of observations in these years (see unbalanced panel data set). That is, changes in the data set at the beginning of the analyzed period can be a severe problem. In our comments, therefore, we take into consideration the period after 2000.

The stable development of technical efficiency in the food processing industry contradicts our expectations. The adjustment processes connected with accession to the European Union, accompanied by important changes in the institutional and economic environments, were supposed to translate into adjustments in the organizational structure and structure of inputs of food processing companies, which would have an impact on technical efficiency. The breakdown of technical efficiency into its components does not provide any information about a significant change either. Technological change did not contribute to the development of technical efficiency, and the scale and management effect changed only slightly in the analyzed period. However, the situation is different in individual branches of the food processing industry.

The development of technical efficiency in slaughtering is almost identical to the development in the food processing industry. The only differences are a small decline at the end of the analyzed period, and the contribution of the management and scale effect. The negative effect of management suggests that companies in the slaughtering industry have problems with the adjustment processes. On the other hand, the positive scale effect suggests that the companies were improving the scale of production. The dairy industry experienced the same development trends as slaughtering. The only difference is a small positive change in technical efficiency in the last year. The development of technical efficiency in the milling industry was quite volatile, with a significant decrease in technical efficiency at the end of the analyzed period. Changes in technical efficiency were determined by both the management and scale effects. The contributions of these effects were rather random. The main factors determining the developments in the milling industries were the exploitation of unused production capacities and the impact of weather on the quality of raw materials. Technical efficiency in feedstuffs increased significantly in 2005; however, this positive change was almost reversed by a decrease two years later. The changes in technical efficiency were determined by the management and scale effects. Their contribution was largely volatile. Whereas management contributed positively and the scale effect negatively in 2005, the opposite was true in 2007. The rather random development in this industry is the result of changes in the quantity of production. Finally, the development of technical efficiency in beverages has a slightly decreasing trend, which was positively determined by the management effect and negatively by the scale effect. The decreasing trend in technical efficiency in beverages is largely a result of considerable structural changes in the industry.

As far as technological change is concerned, the common feature of all analyzed branches of the food processing industry is that it did not contribute significantly to the development of efficiency in the analyzed period. However, the distribution of technical change suggests that the gap between the best and worst food processing companies increased within the analyzed period.

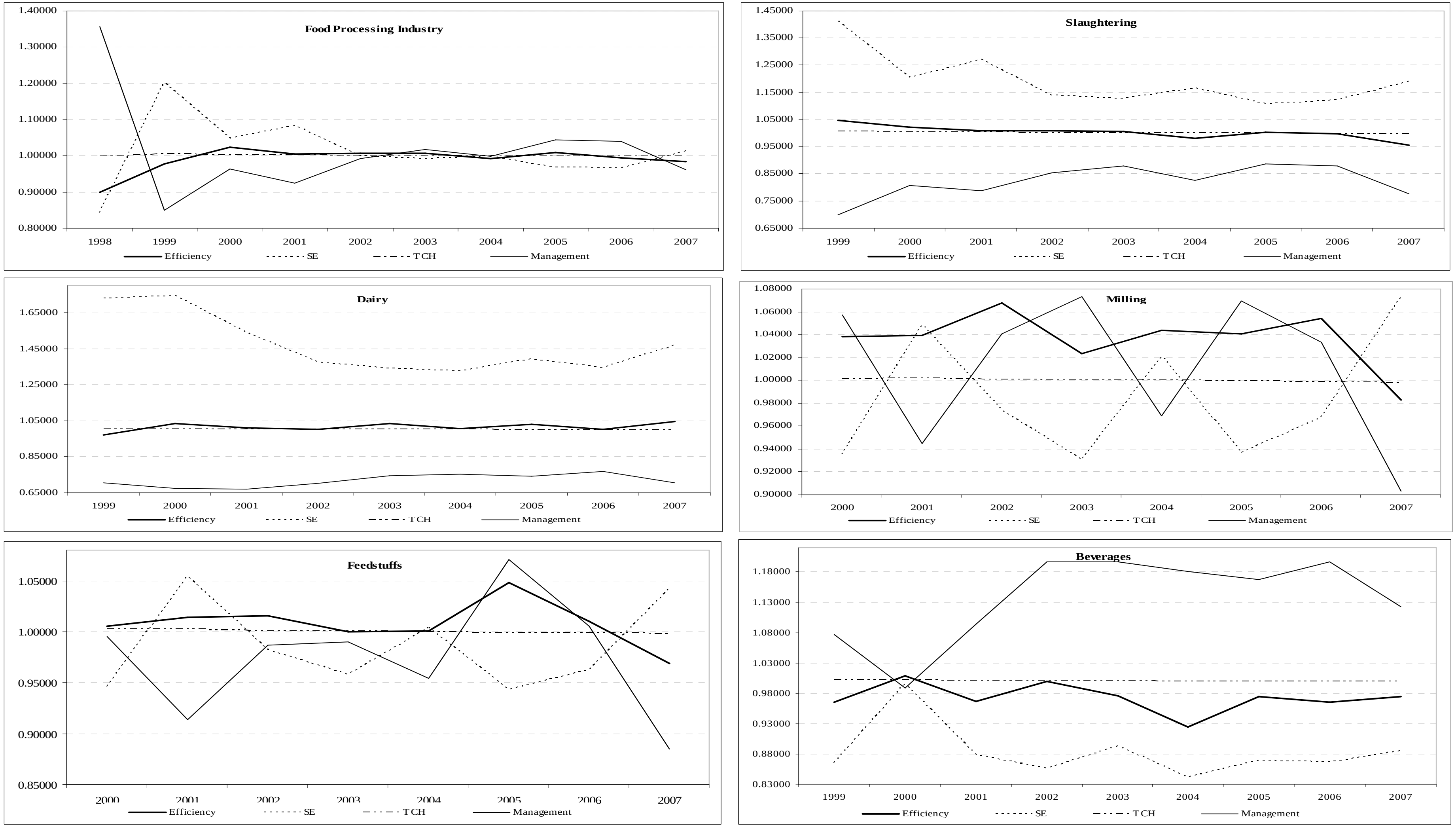
3.3 TFP development

Figures 2a through 2f present the development of TFP in the food processing industry, according to its branches. The figures on the left-hand side provide TFP development without the technical efficiency component. The figures on the right-hand side show the TFP with all its components. The technical efficiency component is added using the decomposition of technical efficiency into technological change, management effect and scale effect.

TFP development in the food processing industry shows an increasing trend. An increase in productivity was positively determined by technological change and the management effect, especially in the last three years. The positive effect of technological change on productivity is a common feature for all analyzed industries at the end of the analyzed period. That is, we cannot observe sector-specific effects. This suggests that the improvement in production possibilities was due more to the diffusion of knowledge generated in another part of the economy, or imported from abroad, than to the sector's own research and development. Moreover, 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 figures for individual sectors show some differences among the analyzed sectors. The drop in technical efficiency in slaughtering at the end of the analyzed period lowered the positive change in productivity. This suggests that an increasing trend in the import of meat products can have a significant negative impact on the competitiveness of slaughtering companies. The dairy industry experienced a calm positive trend in TFP, with a significant positive contribution from scale effect and a negative contribution from management effect. TFP development in the milling and feedstuffs industries was significantly determined by a rather random development in technical efficiency. Unlike in the slaughtering and dairy industries, the management effect contributed positively, and the scale effect negatively, to productivity development in the milling, feedstuffs and beverages industries.

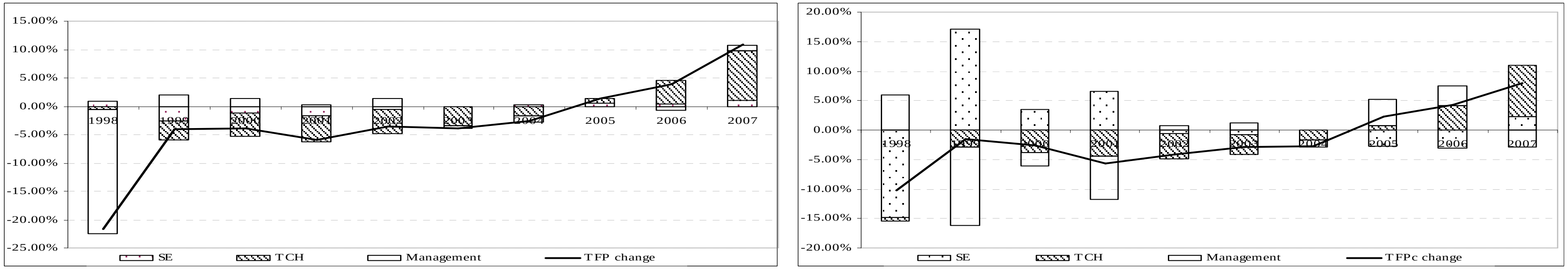
Figure 1: Technical efficiency development in food processing industry and by individual branches



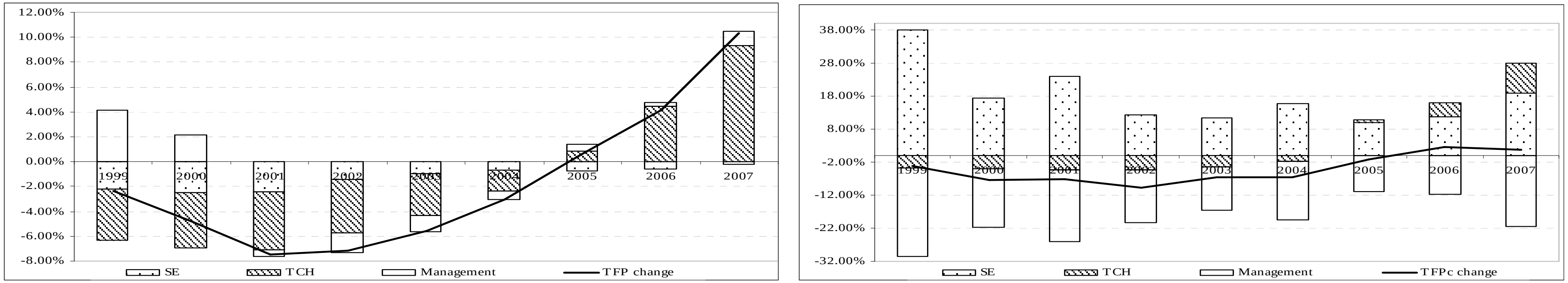
Source: own calculations

Figure 2: TFP development in food processing industry and by individual branches

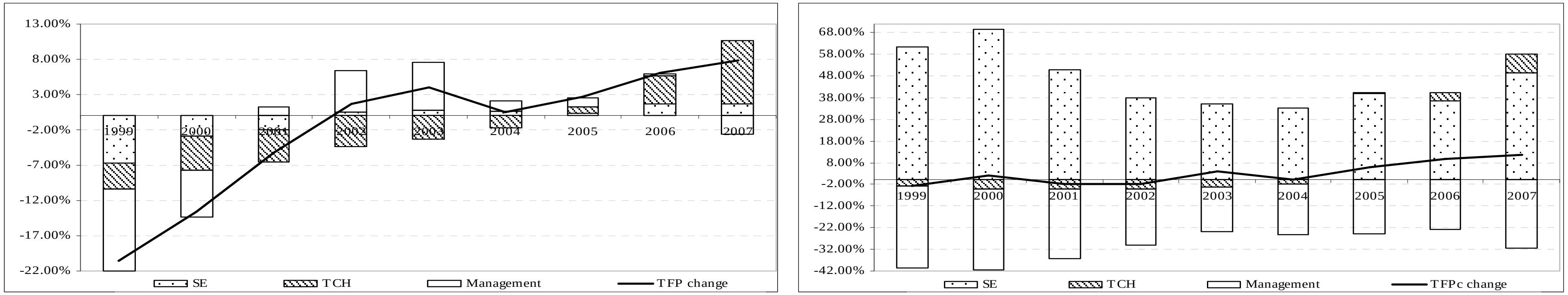
a) Food processing industry



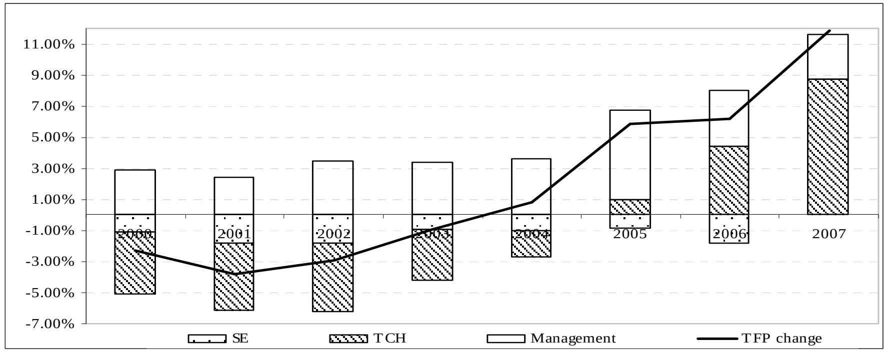
b) Slaughtering

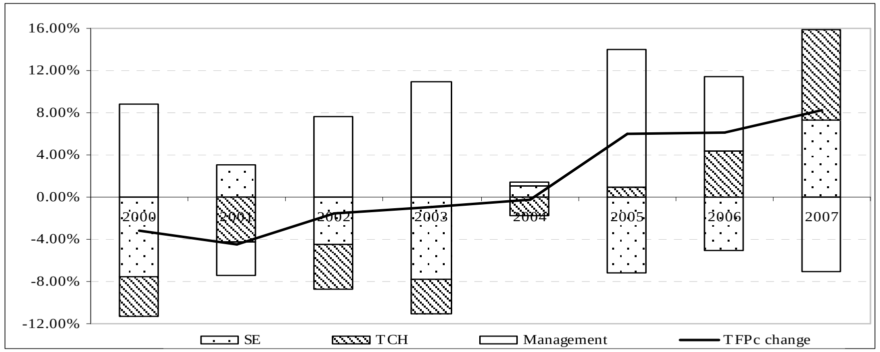


c) Dairy

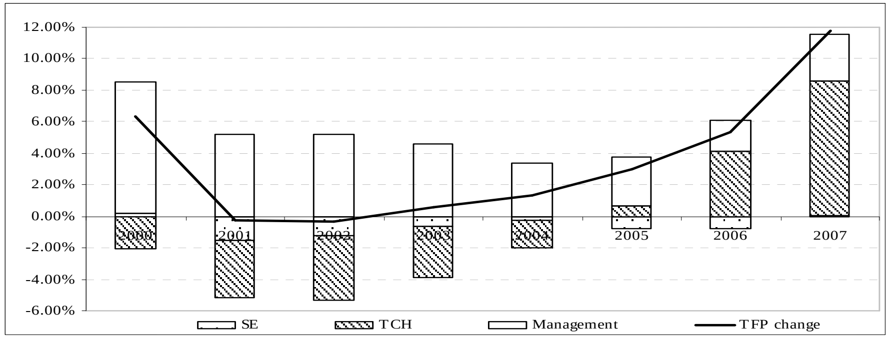


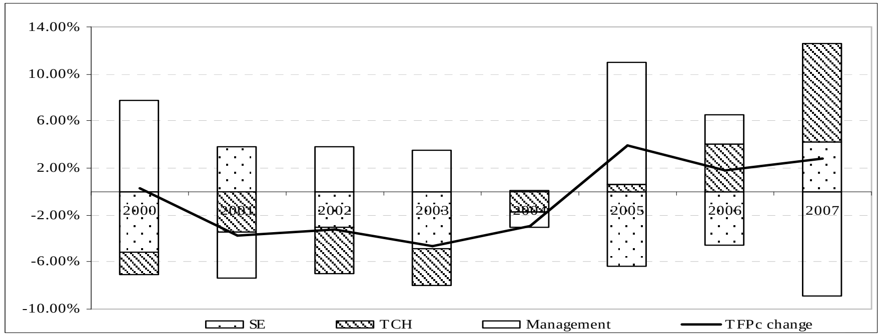
d) Milling



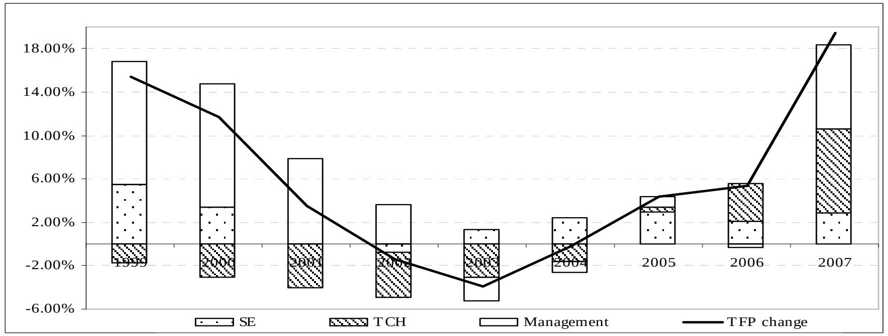


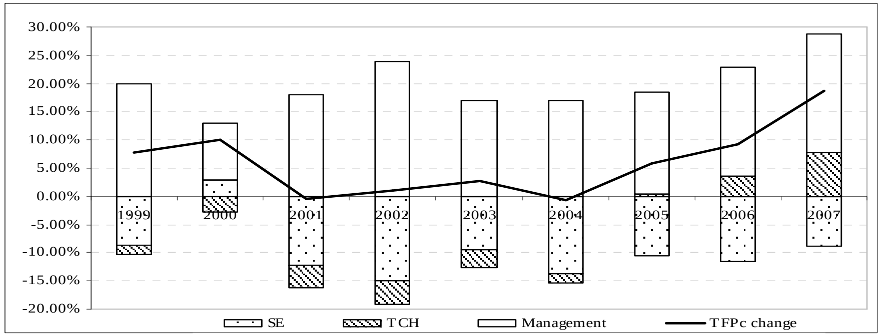
e) Feedstuffs





f) Beverages





Source: own calculations

4 Conclusion

In this section we will concentrate on the questions raised in the introduction, namely the ones regarding the identification which food processing industries are following a path of sustainable development, characterized by the adoption of innovation and reduced waste of resource due to inefficient input use, and the identification of factors determining the development in analyzed industries, regarding the contribution of technological change to productivity development and the assessment to which extent the technological change contributed to the changes in TFP.

Technical efficiency in the food processing industry did not change significantly within the period from 2000 to 2007. The same holds for slaughtering and dairy industry. Milling, feedstuffs and beverages experienced rather random development of technical efficiency. The common feature of all analyzed branches of the food processing industry is that the technological change did not contribute significantly to the development of efficiency in the analyzed period. However, the distribution of technical change suggests that the gap between the best and worst food processing companies increased within the analyzed period.

TFP in the food processing industry significantly increase within the analyzed period. The technological change was an important factor determining the TFP increase at the end of the analyzed period. Since the positive effect of technological change on productivity was a common feature for all analyzed industries this implies that we cannot observe sector-specific effects. This suggests that the improvement in production possibilities was due more to the diffusion of knowledge generated in another part of the economy, or imported from abroad, than to the sector's own research and development. The reason can be found in the compliance process as well as strong economic growth.

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