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Technical efficiency of the food and drink industry and its determinants

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Abstract: This study focuses on evaluating the technical efficiency (TE) of food and drink companies in the Czech Republic and on finding its determinants. The analysis is based on the data of 597 firms and uses the stochastic frontier method. We have identified the key players in the market and the less effective groups of processors. Foreign-owned companies have a strong position because of a better economy, but the results showed that their efficiency is comparable with that of Czech-owned companies. The results helped confirm that the size of the company influences its TE. The lowest efficiency was observed in small companies. TE also differed among branches of the food industry. The highest efficiency was in the bakery and milk industries, and the lowest efficiency was in fruit and vegetable processing. Subsidised firms reached a significantly higher efficiency. With respect to economic results, there is still a need to improve competitiveness through investments.

Keywords: business; competitiveness; food processing; stochastic frontier analysis; subsidies; technical efficiency

The food industry is an important contributor to a nation's economic growth (Menrad 2004). The food processing sector in the Czech Republic is a key part of the national economy not because of its size **(**the food processing sector, including tobacco products, contributed 2.19% to the gross domestic product and 2.53% to employment in 2019**),** but because it is an irreplaceable link in the food value chain. The food industry is related to agriculture and processes its raw materials, which ensures nutrition for the population. Therefore, this sector depends on agricultural development (Seung-Yong 2016).

The position of the Czech Republic's food industry in the European Union (EU) single market is not favourable, and a complex evaluation of its efficiency is required to find the main determinants of this position. According to the latest data from 2018, the labour productivity, wages and turnover per person of the Czech food processing companies reached 50% of the EU-28 average, and the investment activity per person employed is 60% compared with the EU-28 average (Eurostat 2020). The Czech food industry needs to be efficient and competitive in the single market. Economic performance can be improved through efficiency measures such as technical efficiency (TE) and productivity. TE provides useful information about competitiveness (Abdulai and Tietje 2007) because it compares firms on the basis of their ability to transform inputs into outputs.

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The determinants of efficiency also play an important role because they can indicate the key players in the market. The TE itself and the determinants of TE of various firms have been analysed by many researchers.

The traditional determinant of TE is the size of the firm. Chapelle and Plane (2005) found that a firm's size was a statistically significant determinant of the productive performance of the manufacturing sector (their analysis included the food industry). Margono and Sharma (2006) revealed that, in the food industry, larger firms are not more efficient than smaller firms. Rezitis and Kalantzi (2016) investigated TE and its determinants in the Greek food and beverage manufacturing industry for the period from 1984 to 2007. According to their findings, the level of TE is positively affected by a firm's size. Popovic and Panic (2018) evaluated the TE of Serbian dairy processing, and the results showed that efficient companies exist across all size groups. According to Rudinskaya (2017), differences in efficiency with respect to firm size exist in the Czech food industry. Blažková et al. (2020) found that productivity grows when firms are larger.

The effects of various types of subsidies are also worth considering. In the specific case of wine producers in the Czech Republic, Náglová and Šimpachová Pechrová (2019) found that producers supported by the Rural Development Programme (RDP), in general, were more technically efficient, but the difference was not statistically significant. Dvouletý and Blažková (2019) identified a positive effect of an investment subsidy in the Czech food industry on labour productivity, whereas the effect on total factor productivity was negative. Skuras et al. (2006) identified a negative effect on the Greek food and drink industry. The effects of subsidies on a firm's performance are questionable. They can increase efficiency if they provide an incentive to innovate or switch to new technologies (Harris and Trainor 2005). However, the decrease in TE is higher if the income from subsidies weakens motivation and results in a reduction or lack of effort (Bergström 2000).

The location (country or region) can also affect the efficiency of the food sector, as concluded by Margono and Sharma (2006). Akbasogullari and Duran (2020) also included this factor in their study of food industry efficiency. Location can influence not only the performance but also the productivity and growth. In their Czech study, Blažková et al. (2020) used region as a driver of efficiency. For these reasons, we decided to include region as a factor affecting efficiency.

Legal forms may also be a determinant of efficiency and productivity. Kapelko et al. (2019) found that co-operatives were more efficient than private food manufacturing firms. Margono and Sharma (2006) divided firms into public and private and found that private ownership increased efficiency.

The type of ownership can be an important factor influencing a firm's performance. Náglová and Horáková (2017) identified ownership as a determinant limiting business performance for the bakery industry. According to these results, we can suppose that food and beverage processing firms owned by foreign entities might be more efficient. This determinant can positively affect TE in the food industry (Shamsudin et al. 2011). Harris and Robinson (2003) arrived at the conclusion that foreign-owned manufacturing firms were more productive than domestic ones.

Specialisation accounts for any advantages related to more knowledge in a single production activity that could positively affect a firm's performance (Latruffe et al. 2005). Holyk (2016) identified sectors of the food industry with low TE. In the Czech food sector, TE in different food industry branches was also analysed by Shamsudin et al. (2011), Rudinskaya (2017), Afzal et al. (2018) and Blažková et al. (2020).

Besides the explicitly stated determinants, there is also a firm-specific heterogeneity. Hailu and Tanaka (2015) used data from 2000 to 2009 from Ethiopia and found that firm-specific heterogeneity was particularly significant in the food and beverage industry. Therefore, TE is the best concept for examining the performance of food and beverage processing firms.

The research questions (RQs) about the factors influencing TE in food and beverage manufacturing firms were based on the literature review. The wording of the questions is as follows:

RQ1: Size of the firm: The larger the firm, the higher its TE is because of returns to scale.

RQ2: Type of ownership: Companies with foreign owners are more technically efficient than are those owned by Czech capital.

RQ3: Legal form: There are statistically significant differences among the types of legal forms.

RQ4: Business history: The longer the operation history of a firm, the more efficient its production process is.

RQ5: Branches: There are statistically significant differences among different branches of the food and beverage industry.

RQ6: Subsidies: The companies that draw subsidies from the RDP of the EU are more technically efficient than are the companies that do not draw subsidies.

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RQ7: Regions: There are statistically significant differences in the efficiency of companies across regions of the Czech Republic.

This empirical study concerns the Czech food and drink sector and provides a comprehensive view of the TE of companies and its determinants. The efficiency evaluation can also be considered an important issue with respect to the competitiveness of the industry, and the ability to use the minimum of resources to produce a given output becomes a more important ability for firms.

MATERIAL AND METHODS

Methods. Stochastic frontier analysis (SFA) uses an economic theory of the production function. A firm's production is created using the production factors of capital and labour (and land in agriculture). The shape of the production function can vary. The stochastic specification of the models allows for the decomposition of the error term into two components, one the normal random effect and the other to account for technical inefficiency that we explain by various exogenous variables describing the economic and institutional environment (Chapelle and Plane 2005). SFA requires assumptions about the functional forms of the production function and about the distribution of the error term.

We chose to estimate the Cobb-Douglas (CD) production function, which can be written in a linear form as Equation (1). It is a power function, so the coefficients can be interpreted as elasticities. The sum of the coefficients can show whether there are increasing, decreasing or constant returns to scale.

$$\ln y_{it} = \sum_{j=1}^{J} \beta_j \ln x_{j,it} + u_{it} - v_{it} \quad (1)$$

where: y_{it} – production; β_j – coefficients of the explanatory variables x_j; subscript j (j = 1, 2, ..., J) – number of the explanatory variable (J = 4); subscript i (i = 1, 2, ..., N) – particular firm (N is the total number of firms); subscript t (t = 1, 2, ..., T) – period for which the firm is available for observation; u_{it} – inefficiency term; v_{it} – stochastic term.

The CD production function is easy to estimate and interpret. The Cobb-Douglas's major strengths are its ease of use and its seemingly good empirical fit across many data sets (Miller 2008). Besides, the parameters of the coefficients are elasticities and can be interpreted as a percentage change. The limitations of the CD production function are the inherent assumption of constant elasticity of substitution between the inputs which also implies a constant percentage of income distribution across them (Miller 2008).

We also estimated a true fixed effects (TFE) model (Greene 2005). The purpose of the model was to disentangle firm heterogeneity or firm effects from TE (Kumbhakar et al. 2014). This is an important feature of the model, as the inefficiency effect and the time-invariant firm-specific effect are different and should be separated. Otherwise, the inefficiency could also contain firm-specific heterogeneity, thereby possibly distorting it; thus, inability of a model to estimate individual effects in addition to the inefficiency effect poses a problem for empirical research (Satya and Sriram 2018). Therefore, Greene (2005) proposed the TFE model, which accounts for unobserved firm-specific heterogeneity along with time-varying inefficiency.

The distribution of the inefficiency term was chosen to be truncated normal with mean μ and variance σ_{it}^2 specific for each firm i in time t: $u_{it} \sim N^{+}\left(\mu, \sigma_{it}^2\right)$ and of the stochastic term normal distribution with zero mean and variance σ_v^2: $v_{it} \sim N\left(0, \sigma_v^2\right)$. The mean of the inefficiency captures the heterogeneity that arises from unobserved time-invariant long-term factors. The heteroscedasticity can be in either u_{it} or v_{it} or both (Greene 2005) – σ^2 and σ_v^2 are not constant.

After the estimation of the production function, we checked the parameters to see whether they satisfied economic theory. We then tested the statistical significance of the parameters and the model by using the t-test and F-test, respectively.

TE was calculated by a method from Jondrow et al. (1982) as $\exp\left[-E\left(u \mid e\right)\right]$, where exp means exponential, and E is the expected value of inefficiency, with u conditional on Euler's number (e). The efficiency level of the i^{th} firm ranges between 0 and 1. Firms that are 100% efficient are on the frontier where they produce an optimal amount of output with their technology.

There are two ways to assess the influence of the TE's determinants. First, in one step, SFA can allow for the factors to be included in the function of mean or variance of the technical inefficiency. Generally, it is important to differentiate between inefficiency and unobserved heterogeneity in a stochastic frontier framework when firms operate under diverse social, industrial, and environmental conditions (Hailu and Tanaka 2015). A firm's heterogeneity is captured in the function of the mean of technical inefficiency. We assume that there is a heteroscedasticity present in the one-sided technical inefficiency error component.

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The function of the mean of technical inefficiency μ is presented in Equation (2):

$$\mu = \sum_{k=1}^{K} \delta_k f_{k,it} + \varepsilon \quad (2)$$

where: δ – parameters of each factor k (k = 1, ..., K), which is the number of factors f for i^{th} f in time t; δ_k – parameters of each factor; ε – stochastic term.

Using these covariates lets one examine the marginal effect of these variables on inefficiency (Kumbhakar et al. 2014). The function of the variance of technical inefficiency σ_{it}^2 is presented in Equation (3):

$$\sigma_{it}^2 = \sum_{k=1}^{K} \phi_k f_{k,it} + \varepsilon \quad (3)$$

where: ϕ – parameters of each factor.

The second way to assess the influence of the TE's determinants is to calculate the TE and then include it in a censored Tobit regression as an explained variable.

The Tobit regression for censored samples is a linear function in Equation (4):

$$TE_{it} = \sum_{k=1}^{K} \alpha_k f_{k,it} + \varepsilon \quad (4)$$

where: TE_{it} – TE of the i^{th} firm in time t; α – parameters of factors f.

We used both methods and compared the results. The influence of the determinants on technical inefficiency and efficiency can be seen. When there were dummy variables for categorial determinants (such as legal form, type of ownership, size), the average TE was calculated for groups.

The differences in TE between two sub-samples (domestic and foreign firms) were tested by means of a non-parametric Wilcoxon rank-sum test (H_0: $\mu_0 = \mu_1$) and among other samples (different size of firms, different type of production or specialisation) by means of a non-parametric Kruskal-Wallis test (H_0: $\mu_1 = \mu_2 = \ldots = \mu_r$). The TE is skewed to the left, so the assumption of normality is violated, and non-parametric tests must be used.

Data. The sample contains various numbers of observations per firm in different periods – it is an unbalanced panel. The use of panel data has an advantage in that an increasing number of observations means more degrees of freedom and the change in efficiency over time can be observed.

Most data were taken from the financial statements gathered in the non-public Albertina database kept by Bisnode Česká republika (2019, 2020) company. We focused on the branches called 'Manufacturing of food products' [CZ-Nomenclature of Economic Activities (NACE) 10] and 'Manufacturing of drinks' (CZ-NACE 11).

Originally there were 5 039 observations for 690 firms in the whole sample. However, in the efficiency model, some observations were dropped for various reasons (e.g. when linearising the CD function, there was a logarithm of zero or a negative value which could not be computed). The resulting panel included 4 237 observations for 597 firms. The data were available for the years from 2005 to 2017.

The explained variable, the production, was the amount of revenues from sales. The explanatory variables were the following: x_1 – consumption of material and energy, x_2 – equity (own capital), x_3 – credits (borrowed capital) and x_4 – employees (personal expenses).

This sample was analysed according to different criteria based on a literature review (size, business history, ownership, drawing of subsidies, branch of industry, region). The firms were divided according to their size into small, medium and large enterprises (in line with Commission Recommendation 2003/361/EC of the EU). All necessary information was obtained from the Albertina database.

In the current conditions of a liberalised market, foreign companies can enter local markets easily (Holyk 2016). For this reason, businesses were divided according to ownership type into foreign-owned (in which the owner with more than 50% of shares comes from a country other than the Czech Republic) and Czech-owned (owned more than 50% by Czech capital). The information on ownership was obtained from a non-public database, created on request, consisting of the country of origin of the owners and the capital share of processing firms operating in the Czech Republic. We assumed that the foreign companies were more technically efficient than the domestic firms.

The drawing of subsidies is another criterion influencing TE. One of the main sources of subsidies for food processors is the RDP. More than 12% of the budget is committed to the objective of dealing with producers' competitiveness (European Commission 2020).

We evaluated and included in our research the database of individual beneficiaries of subsidies under the RDP 2007–2013 measure 'I.1.3.1. Adding value to agricultural and food products' and measure 'I.1.3.2. Cooperation for development of new products, processes and technologies (or innovations)' in the food industry. We also included the following RDP 2014–2020 mea-

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sure '4.2.1 Processing and marketing of agricultural products' and measure '16.2.2 Support for the development of new products, processes and technologies in the processing and marketing of agricultural products' The businesses in the sample were divided into supported and non-supported ones. The supported businesses received at least a one-time investment subsidy. The non-supported companies had never drawn any subsidies from the RDP. The investment supports should contribute to higher competitiveness of the sector and efficiency of production. We supposed that firms with subsidies would have a higher TE than those of the non-supported companies because of the possibility of drawing support for their investment and technologies, which could help them be more competitive in the market.

The data on the business history of each company were taken from the Albertina database, where it is possible to find the exact year of the company's establishment. The business history states how many years the company has existed in the market.

The same database provided the data on the types of companies. The firms were divided into co-operatives, joint-stock companies, limited companies and public companies.

Efficiency also can differ across regions. The data on the regions (the residence of firms) were obtained from the Albertina database and were divided into 14 regions of the Czech Republic at level 3 of the Nomenclature of Territorial Units for Statistics.

The exact branch of food processors was also used as a criterion. The information was taken from the Albertina database. The firms were divided according to food industry branches (NACE) into 'Manufacture of food products' and 'Manufacture of beverages'.

Most firms were limited liability companies (n = 2 982), followed by joint-stock companies (n = 1 178). There were 42 public companies and 35 co-operatives. The average business history was 19 years (minimum 2 years and maximum 42 years). There were 3 706 observations regarding Czech firms; the remaining companies were foreign-owned. A total of 202 firms received subsidies, the rest of the companies were not granted any subsidies. There were 2 415 small, 1 457 medium and 365 large firms.

Table 1 provides information about the representativeness of the sample. The total population of food industry firms cannot be used because this study covers only legal entities. Therefore, the representativeness was compared across the total number of legal entities from the Albertina database.

Table 1. Representativeness of the sample

CZ-NACE	Population	Sample	% of analysed
NACE 10.1	684	153	22.37
NACE 10.2	21	15	71.43
NACE 10.3	74	61	82.43
NACE 10.4	15	5	33.33
NACE 10.5	138	41	29.71
NACE 10.6	213	26	12.21
NACE 10.7	1 250	156	12.48
NACE 10.8	757	161	21.27
NACE 10.9	289	40	13.84
NACE 11.01	845	38	4.50
NACE 11.02	135	70	51.85
NACE 11.04	4	2	50.00
NACE 11.05	266	58	21.80
NACE 11.06	19	3	15.79
NACE 11.07	68	20	29.41

NACE – Nomenclature of Economic Activities
Source: Own elaboration according to data from Albertina (Bisnode Česká republika 2020)

RESULTS AND DISCUSSION

To assess the determinants of TE, we used two approaches. Both gave analogous results; therefore, we discuss only the second approach (Model B) in detail.

Model A. In Model A, the factors were included in the functions of mean and variance of technical inefficiency. The determinants of the mean technical inefficiency were the type of legal form, business history, and ownership. The variables in the function of the variance of technical inefficiency were the sum of subsidies and the size of the firm.

The model as a whole was statistically significant (Table 2). All parameters of the stochastic frontier were statistically significant and had the expected sign and intensity. If the consumption of material and services increased by 1%, the sales increased by 0.23%. If the equity increased by 1%, the sales increased by 0.07%. When credits increased by 1%, the sales increased by 0.09%, and, finally, if personal expenses increased by 1%, the sales increased by 0.35%.

When the company was a joint-stock company, its mean technical inefficiency was higher; hence, the efficiency was lower than that in other legal forms. If the company had been operating longer on the market, its mean technical inefficiency was lower because it had been well established and its management and produc-

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Table 2. Model A results

Parameter	Frontier		
	coefficient	SE	*P*-value
Production function			
β_1 ($\ln x_{1,it}$) – material, energy consumption	0.2306	2.06E–04	0.0000
β_2 ($\ln x_{2,it}$) – equity	0.0678	7.40E–05	0.0000
β_3 ($\ln x_{3,it}$) – liabilities	0.0920	1.12E–04	0.0000
β_4 ($\ln x_{4,it}$) – personal expenses	0.3534	1.54E–04	0.0000
Inefficiency mean function			
δ_0 (constant)	–129.9408	28.3101	0.0000
δ_1 (joint-stock company)	65.7481	20.7400	0.0020
δ_2 (limited liability company)	54.1578	19.8037	0.0060
δ_3 (business history)	–0.9466	0.3350	0.0050
δ_4 (ownership)	–5.5313	4.4638	0.2150
Inefficiency variance function			
ϕ_0 (constant)	2.9252	0.1680	0.0000
ϕ_1 (subsidies expenditures)	3.81E–06	2.65E–06	0.1500
ϕ_2 (small size)	0.4355	0.0593	0.0000
ϕ_3 (medium size)	0.2011	0.0599	0.0010
Stochastic term variance function			
ρ_0 (constant)	–25.1147	2.8854	0.0000
σ_u	5.0796	–	–
σ_v	3.52E–06	5.08E–06	0.4880

β_1, β_2, β_3, β_4 – parameters of explanatory variables x_1, x_2, x_3, x_4; subscript i (i = 1, 2, ..., N) – particular firm (N – total number of firms); t (t = 1, 2, ..., T) – time; δ_0 – constant; δ_1, δ_2, δ_3, δ_4 – parameters of various factors; ϕ_0 – constant; ϕ_1, ϕ_2, ϕ_3 – parameters of various factors; ρ_0 – constant; σ_u – variance of inefficiency; σ_v – variance of stochastic term
Source: Own elaboration according to data from Bisnode Česká republika (2019, 2020), MIT and CZSO (2019, 2020) and SAIF (2019)

tion processes may have been more efficient. If the firm was owned by Czech capital, the technical inefficiency was lower than if it was owned by foreign capital.

When the sum of subsidies increased, the variance of technical inefficiency increased as well. If the firms were small or medium sized, their variance of technical inefficiency was higher than that in large companies. All the results met our expectations.

The estimated TE was 80.42% on average, and the median was 5 percentage points higher – 85.60%.

Model B. In Model B, the TFE model with a truncated normal distribution was estimated, and TE was calculated (Table 3). The TE as an explained variable and factors as explanatory variables were included in the Tobit regression. Model B had frontier parameter results similar to those of Model A. Overall, Model B was statistically significant.

The average TE of food and beverage processing companies was similar to that of the previous model (80.42%), but the median was slightly higher (85.63%).

The development of TE in various years is displayed in Figure 1. The highest value was seen at the beginning of the period in 2005, but it decreased, and the lowest value was achieved in 2010 because of the economic crisis in 2008. Until that time, there was a downward trend. However, the situation subsequently improved, although the average TE was never as high as at the beginning of the period; it reached only the level of 80.68% in 2014.

TE was included in the Tobit regression with determinants as explanatory variables (Table 4). First, all of the determinants were included, but the coefficient for subsidies was not statistically significant because there were only 202 observations with subsidies.

Concerning the coefficients for the constant, joint-stock companies and small firms were statistically significant at the 0.01 level. The coefficients for limited liability companies and medium-sized companies were significant at the 0.05 level. The rest were also significant but only at the 0.1 level.

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Table 3. Model B results

Parameter	Frontier		
	coefficient	SE	*P*-value
Production function			
β_1 ($\ln x_{1,it}$) – material, energy consumption	0.2319	2.80E–05	0.0000
β_2 ($\ln x_{2,it}$) – equity	0.0675	7.89E–06	0.0000
β_3 ($\ln x_{3,it}$) – liabilities	0.0924	9.31E–06	0.0000
β_4 ($\ln x_{4,it}$) – personal expenses	0.3526	2.31E–05	0.0000
Inefficiency mean function			
δ_0 (constant)	–365.0803	97.7615	0.0000
Inefficiency variance function			
ϕ_0 (constant)	4.5860	0.2772	0.0000
Stochastic term variance function			
ρ_0 (constant)	–34.359	23.6568	0.1460
σ_u	9.9046	1.3259	0.0000
σ_v	3.46E–08	4.09E–07	0.9330
λ	2.86E+08	1.3300	0.0000

β_1, β_2, β_3, β_4 – parameters of explanatory variables x_1, x_2, x_3, x_4; subscript i (i = 1, 2, ..., N) – particular firm (N – total number of firms); t (t = 1, 2, ..., T) – time; δ_0, ϕ_0, ρ_0 – constants; λ – ratio of the variance of inefficiency σ_u to the variance of stochastic term σ_v, indicating that, the one-sided error term u dominates the symmetric error term v and the variations in the actual production is due to differences in food producers' practices rather than random variation

Source: Own elaboration according to data from Bisnode Česká republika (2019, 2020), MIT and CZSO (2019, 2020) and SAIF (2019)

The results of the Tobit regression correspond to the results of Model A. If a company was a joint-stock or a limited liability company, the TE was lower than that in public firms or co-operatives. If the business history increased by 10 years, then the efficiency increased by 0.0011%. If the company was owned by Czech capital, the efficiency was higher. If the company was a small or medium-sized company, the efficiency was lower compared with that in large firms.

Finally, we tested the differences in various groups (Table 5).

Ownership. In 2018, almost 370 foreign enterprises operated in the Czech food and beverage market, and their share in the total number of firms in this industry was 3.4%. Most of the foreign companies operated in '10.8 Production of other products', '10.7 Bakery industry' and '10.5 Milk industry' (MIT and CZSO 2019). The foreign owners were mainly from the Netherlands, Germany, Slovakia, and Austria. As concerns the beverage industry, most of the firms in the beer industry were owned by foreign capital, which means that mainly Czech processors operate in the domestic market. Despite their low share in terms of business structure (number of enterprises), foreign companies employed 24% of people in the food and drink industry. Their share of sales was also important (36%). The average wage was 53.6% higher than in the Czech-owned companies [analysis based on MIT and CZSO (2019) data and Bisnode Česká republika (2019)]. Despite their very good economic results (higher labour productivity, higher sales per employee or wage), as also stated by Shamsudin et al. (2011) and Harris and Robinson (2003), the efficiency of foreign companies according to the results was comparable with that of the Czech-owned companies. According to the results of the Wilcoxon rank-sum test, the differences between the group of firms owned by Czech capital and the group of firms owned by foreign capital did not reach the level of statistical significance of 0.05. According to Holyk (2016), there is evidence that domestic processors face competition from foreign companies in the market. Shamsudin et al. (2011) stated that the current ongoing liberalisation of trade creates fewer barriers for internationalisation and it is easier to place foreign products in the domestic market. Competition in the local market can be harsh. Our results showed no statistically significant differences at the 0.05 level (Wilcoxon rank-sum test). Benfratello and Sembenelli (2006) also found that the efficiency of Czech processors was comparable to that of foreign processors.

Subsidies. One of the main sources of subsidies in the food and drink industry is the RDP [measure 4.2.1 (for-

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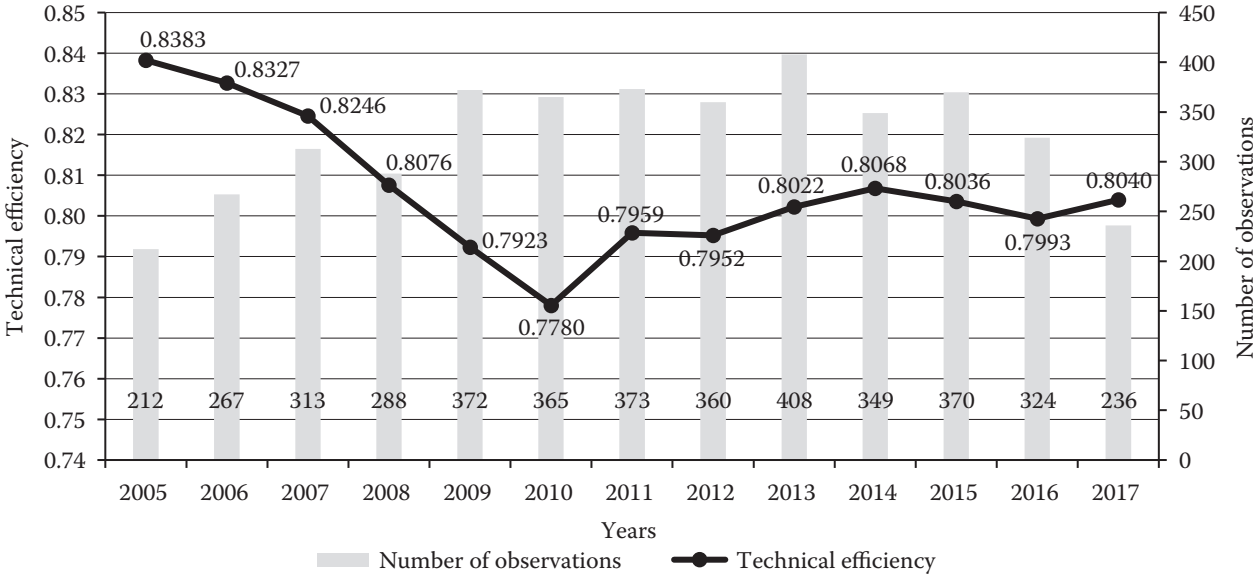

Figure 1. Development of technical efficiency in years 2005–2017

Source: Own elaboration according to data from Bisnode Česká republika (2019, 2020), MIT and CZSO (2019, 2020) and SAIF (2019)

mer I.1.3.1) and measure 16.2.2 (former I.1.3.2)] for large companies and innovative projects. The applicants under measure 4.2.1 in the current period 2014–2020 are micro-enterprises and small enterprises (almost 80% of applications). Most beneficiaries according to the current data were from the meat industry (47%), processing of vegetables and fruit (17%) and the milk industry (9%). In the drink industry, the applicants were engaged mainly in wine production. The highest investments per beneficiary realised through an investment subsidy were in the milk and milling industries. The smallest projects were in the meat industry [analysis based on data from SAIF (2019)].

The efficiency of the firms (observations) which were granted a subsidy was slightly higher (average, 80.48%) than that of firms that were not subsidised at all (average, 79.23%). The differences between the subsidised and non-subsidised firms were statistically significant at the 0.1 level. The same results were obtained by Náglová and Šimpachová Pechrová (2019). By helping Czech companies implement new technologies and innovations and produce more effectively, investment subsidies can help the Czech food and drink industry become more competitive in both local and foreign markets. The same was also confirmed by Rodgers (2011); subsidies help the food and drink industry increase its competitiveness. The support enabled them to be more technologically intensive and effective; however, its effect on efficiency was not clear. Cerqua and Pellegrini (2014) found positive effects of subsidies on efficiency in the food industry, but Harris and Trainor (2005) and Skuras et al. (2006) found negative effects. Subsidies can also weaken the motivation to produce more effectively if the income from subsidies is higher (Bergström 2000). Any future research should be focused on the effect of subsidies on TE in different branches of industry and types of grants.

Size. In 2019, there were mostly small businesses in the Czech food industry (they constituted 95% of total businesses), and the same applied to the drink industry (98% of businesses). Together with medium-sized enterprises, they offered jobs for 66% of people in the food industry and 57% in the drink industry. Their share in total sales was 61% in the food industry

Table 4. Tobit regression results for Model B

Parameter	coefficient	SE	*P*-value
α_0 (constant)	–0.0690	0.0229	0.0030
α_1 (joint-stock company)	–0.0459	0.0224	0.0410
α_2 (limited liability company)	0.0011	0.0006	0.0600
α_3 (business history)	0.0180	0.0093	0.0530
α_4 (ownership)	–0.0663	0.0116	0.0000
α_5 (small size)	–0.0233	0.0115	0.0440
α_6 (medium size)	0.8642	0.0288	0.0000

α – estimated parameters of factors

Source: Own elaboration according to data from Bisnode Česká republika (2019, 2020), MIT and CZSO (2019, 2020) and SAIF (2019)

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Table 5. Differences in technical efficiency according to Model B

Variable	Observations	Mean	SD	Kruskal-Wallis/Wilcoxon test	
				χ^2-value/z-value	P-value
Whole sample	4 237	0.8042	0.1951	–	–
Type of company					
Joint-stock company	1 178	0.7988	0.2003		
Co-operative	35	0.8221	0.1552	8.7050	0.0335
Limited liability company	2 982	0.8048	0.1943		
Public company	42	0.8960	0.0918		
Type of ownership					
Other countries	531	0.8008	0.1901	–0.9630	0.3355
Czech owner	3 706	0.8047	0.1959		
Subsidies					
Supported from RDP	4 035	0.8048	0.1957	1.7330	0.0831
Non-supported from RDP	202	0.7923	0.1835		
Size of a firm					
Small	2 415	0.7858	0.2084		
Medium	1 457	0.8252	0.1764	26.3480	0.0001
Large	365	0.8420	0.1588		
Branch					
NACE 10.1	772	0.8169	0.1772		
NACE 10.2	38	0.7480	0.2741		
NACE 10.3	429	0.7159	0.2490		
NACE 10.4	40	0.7650	0.1492		
NACE 10.5	194	0.8244	0.1785		
NACE 10.6	162	0.7522	0.2013		
NACE 10.7	683	0.8576	0.1705		
NACE 10.8	824	0.8238	0.1793	161.6840	0.0001
NACE 10.9	255	0.8184	0.1493		
NACE 11.01	112	0.7286	0.2580		
NACE 11.02	317	0.7603	0.2166		
NACE 11.04	6	0.8100	0.1110		
NACE 11.05	242	0.8183	0.1791		
NACE 11.06	31	0.7935	0.1584		
NACE 11.07	132	0.7998	0.1697		

RDP – Rural Development Programme; NACE – Nomenclature of Economic Activities

Source: Own elaboration according to data from Bisnode Česká republika (2019, 2020), MIT and CZSO (2019, 2020) and SAIF (2019)

and 41% in the drink industry. Nonetheless, the labour productivity of small and medium-sized enterprises was lower than that in large companies [analysis based on MIT and CZSO (2020) data].

The differences in TE among the firms of various sizes were statistically significant [as was confirmed, for example, by Chapelle and Plane (2005)]. The lowest efficiency was noted in small companies in the food industry (78.58%), as Popovic and Panic (2018) also concluded. They indicated higher efficiency in this group (up to 90.7%). According to our expectations, large companies were the most technically efficient (84.20%), and Popovic and Panic (2018) had similar results, with more than 90% – the larger the firm, the higher the efficiency. Blažková et al. (2020) reached the same result for Czech food processing, and Rezitis and Kalantzi (2016)

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also found a positive effect. However, Margono and Sharma (2006) reached the opposite results; according to them, the larger firms in the food industry were not more efficient than smaller firms. Small businesses are a very important part of industry in the Czech Republic, but their economic results are not comparable with those of larger enterprises because small companies can suffer from input inefficiency and insufficient size, whereas bigger companies can be overinvested (Popovic and Panic 2018). Smaller firms could increase their size to be more effective and find an optimal level of productivity.

Branch of industry. We found statistically significant differences among the NACE branches. According to Blažková et al. (2020), differences in productivity in Czech processing reflect different market and production conditions. The highest average TE (85.8%) was observed in the manufacture of bakery and farinaceous products (NACE 10.7). Rudinskaya (2017) identified an average TE in the Czech bakery industry of only 71.01%. Afzal et al. (2018) identified disproportion in this sector. The bakery industry was one of the key branches in the Czech food industry because its share in the total number of enterprises was 45% (2019), in the number of employees was 34% (2019) and in sales was 14% (2019). There has been a long-term decrease in the number of employees. In comparison with other branches of industry, the bakery industry is characterised by very low labour productivity [analysis based on MIT and CZSO (2020) data]. Therefore, there is a great need to invest in new technologies and innovations to be more competitive and to replace human labour with machines.

The second-best efficiency (82.4%) was reached by the milk industry (NACE 10.5). Afzal et al. (2018) and Rudinskaya (2017) also identified high performance in this sector. Holyk (2016) found a very low efficiency for the milk sector; according to her, this branch contributes to the lower performance of the food industry, but she identified almost the same level of efficiency as we did in this study. In 2019, this branch of industry employed 10% of people in the food industry and accounted for 2% of businesses. The share of total sales (17%) and very good labour productivity were also important findings [analysis based on MIT and CZSO (2020) data].

Another important sector of the Czech food industry is meat processing. In 2019, the meat industry employed 23% of people in the whole food sector and had a 25% share in the food industry business structure (in both cases, the second largest share after the bakery industry). This sector is the main contributor to the total sales of food processing (MIT and CZSO 2020). However, it faces the same problems as the bakery industry (low labour productivity, low wages, decreasing number of employees). Results showed that its efficiency was among the best in the food sector (81.69%). Holyk (2016) argued that the meat industry had low efficiency and was underperforming, with an efficiency lower than 75%, and Rudinskaya (2017) stated that the efficiency of the Czech meat industry was 69.47%.

The lowest efficiency (71.6%) was in the processing and preserving of fruit and vegetables (NACE 10.3). The economic situation in this sector was not very good, with a very low labour productivity and share of sales in the food industry [analysis based on MIT and CZSO (2020) data].

The key branch in the Czech beverage industry was the manufacture of beer (NACE 11.05). This branch employed almost 50% of people in the beverage industry in 2019 and its share in the total sales was more than 52%. Another characteristic was the very high labour productivity [analysis based on MIT and CZSO (2020) data]. These results correspond to the highest TE (81.83%). Very good efficiency was also reported in the production of non-alcoholic drinks (11.07%), which was also in a good economic position. The share of wine producers (NACE 11.02) in the number of businesses was 10% in 2019, and they were the major beneficiaries of subsidies from the RDP in the drink industry (SAIF 2019; MIT and CZSO 2020). Their TE was 76.03%. Shamsudin et al. (2011) and Afzal et al. (2018) also confirmed the high efficiency of the alcohol and soft drink industry.

Legal form. If we calculate the TE according to a company's legal type, it is obvious that the highest TE was achieved by public companies (89.60%) and co-operatives (82.21%). The least efficient were joint-stock and limited liability companies. However, there was very high variability in the sample, and the highest number of observations was in public companies and co-operatives because they are very common legal forms.

The efficiency of limited liability and joint-stock companies was lower on average, even though they formed a larger group. We can assume that when there are more firms, the existence of less efficient firms among them is also more likely. Using a Kruskal-Wallis equality-of-populations rank test, we concluded that the differences were statistically significant.

Business history. The history of a firm can be an important determinant because firms with a long business history are assumed to be more effective because of their tradition, market knowledge and created consumer base. This assumption was confirmed because

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Figure 2. Map of (A) technical efficiency and (B) number of observations in regions

Source: Own elaboration according to data from Bisnode Česká republika (2019, 2020), MIT and CZSO (2019, 2020) and SAIF (2019)

the more effective firms were those with a business history of 24, 25, and 26 years – one of the oldest firms in the sample. Conversely, Dumont et al. (2016) found that efficiency growth decreases with firm age; starting firms are not that efficient and achieve efficiency later as they grow. Pervan et al. (2017) added that older firms in the food industry benefit from knowledge and other aspects of business but also can have difficulties caused by inflexibility, routines, and osseous organisational structure. Research also has shown that very young firms (with history of 4, 5, 7, and 9 years) have high efficiency. These companies are quite new to the market and can be attractive for consumers who like to try new or innovative products. Blažková et al. (2020) also found that older firms in the Czech food industry had a higher productivity (valid until the age of 12.5 years) and that the growth of productivity was higher in young firms. These results are comparable to the research re-

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sults we present here. The position of young firms in the market can be evaluated as very good, whereas Akbasogullari and Duran (2020) found the opposite. They recommended subsidising young food industry firms. Margono and Sharma (2006) found different results; in their sample of food processors, they found no effect on efficiency with respect to firm age.

Region. The differences in TE according to the region where the firms operated were also tested, and they were statistically significant. The average TE in different regions is displayed in Figure 2. The highest efficiency was achieved in the Pardubický (85.76%), Plzeňský (84.90%) and Vysočina (83.81%) regions. The lowest efficiency was observed in firms in the Karlovarský (75.63%) and Olomoucký (76.13%) regions. Blažková et al. (2020) used this determinant in Czech food processing, but they did not find any significant differences. Margono and Sharma (2006) identified region as a factor that did not affect efficiency.

CONCLUSION

In this study, we provide a thorough analysis of drivers of TE in the Czech food industry. We identified the key groups with a higher efficiency that are supposed to be competitive in the market. We have also highlighted the groups of enterprises with room for efficiency improvement; their competitiveness can be affected because of their less effective use of inputs.

Business size, legal form, branch of industry, region and subsidies can be considered as factors determining TE. We did not find significant differences in TE between Czech- and foreign-owned processors. Their efficiency was comparable.

Efficiency can be influenced by investment activity, which is needed in the food industry with respect to the lack of human resources and lower labour productivity. The results revealed that subsidised firms had a higher TE than did the non-subsidised companies. Investment subsidies helped producers be more competitive by implementing technologies and using production factors effectively. The Czech food industry consists mainly of small enterprises with low efficiency, so there remains a need to support small firms in particular. Subsidies are beneficial for them because of the access to technologies that might otherwise be beyond their financial capacity. It is also necessary to support technologies or innovations contributing to a higher value added to reach better economic results and savings. Support for some regions might also be useful because significant differences were also found there.

A very good efficiency was identified in businesses with a longer history (24 years and more) and in firms existing no longer than 9 years. In firms with a longer history, good efficiency was due to their established position and strong presence in the market, as well as their experience. The category of young processors is an important part of food processing with respect to its development and growth [as also stated by Blažková et al. (2020)].

TE also differed among branches of the food industry. The highest was in the bakery and milk industries, and the lowest was in fruit and vegetable processing. The bakery and milk industries, together with the milling industry, should receive greater preference when applying for subsidies. The current preferential criteria (points that are necessary to become eligible for a subsidy) should be more flexible. They give preference mostly to milk producers (the highest number of points), then to meat, fruit, vegetable, hops, wine, and feed producers (same level of points).

In conclusion, with respect to the results of this study, we recommend use of investments because, among other things, they can help a firm grow, solve the lack of human resources or enable the use of modern technologies. These factors play an important role in the market to sustain competitiveness and can help the sector grow sustainably.

We also identified some needs for further research. We recommend providing a more detailed analysis to combine some of the criteria we used to obtain more information about efficiency that can contribute to the theoretical knowledge of this sector. For example, it would be useful to evaluate efficiency between branches of industry and different sizes of firms to determine what type of grants, such as subsidies for investment or subsidies for innovation, better improve their efficiency.

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