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**PRODUCTION EFFICIENCY ANALYSIS OF THE HUNGARIAN
MEAT PROCESSING INDUSTRY**

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1 INTRODUCTION

Many high-capacity meat processors went bankrupt in recent years, which is an important industry for the Hungarian economy. János Ruck, former general manager of Gyulai Húskombinát Plc.¹ made a remark that “there is no profitably operating meat processor in Hungary at the time being, all the companies from the largest to the smallest are loss-making” (Rácz, 2012). This picture is distorted by the fact that more than half of the Hungarian meat processors’ and producers’ operating profit was positive in 2011. Compared to other sectors, meat processors’ market performance is not dismal either. However, average operating profit per firm ratio was close to zero in the last decade that may not be sustainable in the long-run.

The above mentioned evidences naturally pose the question that what is the reason behind the poor performance of the Hungarian meat processors. The profitability of a company mainly depends on the decisions made by managers and corporate leaders. However, market structure can influence the performance of a company as well. In our previous research, we conducted a price transmission analysis in the Hungarian meat processing industry, and concluded that price transmission is symmetric and both input and output markets are competitive.

The current research is a continuation of the previous one. Our goal is to analyze whether meat processors made optimal decisions in the years have gone by. In our metric, ‘optimal’ decisions are those that maximize profit. Profit maximization requires efficient production, i.e. producing the maximum level of output using a given level of inputs (or *vice versa*). Further analysis of the meat processing industry will determine whether individual firms made optimal decisions or not.

The result has policy implications given that general and local governments tried to retain jobs by giving financial support to most of the companies. This calls for an immediate analysis of the meat supply chain to understand whether it was inefficient production or other factors which caused the same. The bail-out of inefficient companies will soften their budget constraints and it is very likely that losses will reproduce themselves in this case.

Additionally, there is no detailed production efficiency analysis of the Hungarian meat processing industry, therefore this research will fill this gap.

¹ Gyulai Húskombinát Plc. is one of top 10 meat processing companies in Hungary. It went bankrupt in 2012.

The structure of this paper is as follows. Section 2 gives a short introduction of the Hungarian meat industry. Section 3 presents the theoretical framework of the analysis. Section 4 focuses on previous studies. Sections 5 and 6 describe the methodology and the dataset used, respectively. Section 7 is made up of the results of the analysis. Concluding comments are presented in Section 8.

2 THE HUNGARIAN MEAT INDUSTRY

The meat processing industry is the largest food industry in Hungary. It lies in the middle of the meat supply chain, which begins at the farms and finishes at the consumers (“from farm to fork”, as the title of the Eurostat (2011) statistical book states). This paper focuses on the meat processing industry: inputs are produced by slaughterhouses and outputs are bought by whole sellers and/or retail chains.

Table 1 demonstrates concentration and profitability statistics of the Hungarian meat supply chain in the latest available year. The statistics show that processing is the most concentrated at the vertical level, still, it generated the highest losses. The processing sector is highly concentrated in almost every European country (EC, 2011). A Hungarian specialty is the relatively small foreign ownership compared to other EU countries (Bakucs and Fertő, 2005).

Table 1: Concentration and profitability statistics about the Hungarian meat supply chain (in 2008)

Designation	CR3* (%)	CR5* (%)	HHI**	Operating profit per firm (million HUF)
<i>Processing and preserving of meat</i>	21.08	31.29	279	-6.839
<i>Production of meat and poultry meat products</i>	74.49	82.53	2601	-40.653
<i>Retail sale in non-specialized stores with food, beverages or tobacco predominating</i>	49.9	57.62	1182	0.381

Notes: * based on net sales revenue; ** Herfindahl–Hirschmann Index: sum of squared market shares (in %) based on net sales revenue

Source: Hungarian Competition Authority – Competition statistic database and National Tax and Custom Administration of Hungary

On the other hand, Czibik and Makó (2008) state that more than half of the meat and dairy processors had raised their wholesale prices by more than the inflation rate in 2006. No other food processing sector was so successful with regard to price increases, which can at least partially be caused by the high concentration ratio.

According to a Nielsen survey, 81% of the Hungarian consumers prefer Hungarian meat products, which is the highest ratio considering food products. In addition, private labelled goods have a market share of only 25%, which is moderate compared to other product categories (based on Nielsen data). The rest of the market is occupied by branded

products providing more profit to their manufacturers. These latter figures draw a better picture of the industry and its market perspectives.

3 THEORETICAL BACKGROUND

Production efficiency analysis has a strong microeconomic background. According to the theory of firm, a firm is producing a set of outputs using a set of inputs. Technology describes the transformation method. In this paper we consider a multiple-input, multiple-output firm, i.e. a company that produces more than one output from more than one input.

For a multiple-output production process production technology describes the transformation. Let $S = \{(\mathbf{x}, \mathbf{q}) : \mathbf{x} \text{ can produce } \mathbf{q}\}$ be the technology set, which shows that using input vector $\mathbf{x}$ the given firm can produce an output vector $\mathbf{q}$. S contains all the technologically feasible production technologies.

Defining production efficiency is more straightforward if we let $\mathbf{y} = (-\mathbf{x}, \mathbf{q})$ be the net outputs of the given technology and Y be the production set containing all the feasible technologies (i.e. $\mathbf{y}$). A negative element in $\mathbf{y}$ means an input, a positive element in $\mathbf{y}$ means an output and 0 means that the given product is either not used in the technology or this is only an intermediate product which has zero net output. Using this notation, production efficiency is as follows (Mas-Colell, Whinston and Green, 1995): A production vector $\mathbf{y} \in Y$ is efficient if there is no $\mathbf{y}' \in Y$ such that $\mathbf{y}' \geq \mathbf{y}$ and $\mathbf{y}' \neq \mathbf{y}$. It follows that a given technology is efficient if there is no other feasible technology that generates more outputs (at least from one of the outputs produced by the firm) using the same quantity of inputs or generates the same outputs using less inputs. The expected profit maximization behavior of the firm is strongly related to efficiency. If a production vector $\mathbf{y} \in Y$ is profit maximizing, then it is also efficient. The converse of this statement is also true, but only if Y (i.e. the production set) is convex. In this case all the efficient technologies are also profit maximizing. The proof of these propositions can be found in many papers and books (e.g. Mas-Colell, Whinston and Green, 1995).

However, this definition of efficiency covers only one aspects of efficiency, namely technical efficiency. There are several other types of efficiency should be taken into consideration (Coelli et al., 2005). Allocative efficiency reflects to whether the firm uses the inputs in optimal proportion, i.e. whether costs can be reduced using a different combination of inputs (leaving the output level constant) or not.

Scale efficiency reveals whether the firm's scale is optimal or not. If the firm uses a globally constant return-to-scale technology then this company is automatically scale efficient, otherwise may not. In this paper, we only analyze technical and allocative

efficiency (hereinafter together referred to as economic efficiency). Scale efficiency is out of the scope of this paper.

Technical efficiency can be calculated using two different approaches. Input-oriented efficiency shows which is the amount of proportionate input reduction that makes still possible to produce the same level of output. Output-oriented efficiency is concentrated on output increase that is possible using the same input quantities.

Input-oriented efficiency is more connected to cost minimization and finding the overall cost efficient technology. On the contrary, output-oriented efficiency is rather connected to profit maximization and finding the overall revenue efficient technology (leaving cost elements unchanged). However, profit maximization is not completely equal to overall revenue efficiency, but profit efficiency methods did not become popular and widely used. Finally, as we mentioned it earlier in this chapter, if the technology set is convex then economic efficiency means profit maximization at the same time.

4 LITERATURE REVIEW

Production efficiency analysis has a large theoretical and empirical literature. In this section, we will review two main areas of this literature. First, the comparison of the performance of stochastic and deterministic models mainly conducted using Monte Carlo simulations will be shown. Second, some interesting and relevant efficiency analyses will be introduced. These prior studies will help to find the most appropriate model and assumptions for our analysis.

4.1 THE COMPARISON OF STOCHASTIC AND DETERMINISTIC PRODUCTION EFFICIENCY APPROACHES

There are several methods to estimate production efficiency. The two most wide-spread approaches are data envelopment analysis (DEA) and stochastic frontier analysis (SFA). The former one is a mathematical programming approach, a non-parametric method to estimate the efficiency of a given set of companies (or countries, etc.). The latter one is an econometric approach, a so-called parametric model, which requires the estimation of a production or cost function.

Comparing these two types of models, both of them have pros and cons. DEA is a rather deterministic approach that assumes no measurement error, no statistical noise and no other random conditions. On the contrary, SFA can also be used if the data contains some statistical noise. Real world data often contain some measurement errors, therefore the econometric estimation of a production function can be more favorable.

However, DEA requires no assumptions with regard to the distribution of the inefficiencies or the exact form of the production function, therefore this is a more robust approach compare to SFA.

Banker, Gadh and Gorr (1993) compare the two methods using Monte Carlo simulations. Their conclusion is that DEA performs better if the sample size and the variation of the measurement error is small. SFA is the preferred method if sample size is larger (more than 100) and measurement errors are also larger. In general, if real world conditions and SFA assumptions are in line with each other, then stochastic models are more accurate. Banker, Gadh and Gorr (1993) also state that the minimum sample size is 50 for a stochastic frontier analysis.

Ruggiero (1999) also use Monte Carlo simulation to compare the performance of stochastic and deterministic models. Surprisingly, he comes to the conclusion that DEA is better performing in almost every cases. However, the flexible translog functional form of the SFA shows good performance if the sample size is large (more than 100). It is important to note that Banker, Gadh and Gorr (1993) use mean absolute deviation and the Wilcoxon signed rank test as a measure of performance, while Ruggiero (1999) use rank correlation. The difference with regard to the final conclusion can be affected by the different performance criterion used.

A recent study of Krüger (2012) compares the estimation performance of the two “old” models and a newer, non-parametric-stochastic model. Krüger (2012) uses Monte Carlo simulation with 1000 replications which is significantly higher than the replications used in previous studies. The results show that SFA is outperforming all the other methods considered in the analysis. Additionally, SFA methods are less sensitive for the changes of the Monte Carlo simulation settings. The only exception is the introduction of outliers. Overall, Krüger (2012) states that the new methods are not performing better than the traditional SFA or DEA at least in the design of the Monte Carlo simulation used.

The previous analyses used cross section data, however, production efficiency analyses are more often conducted using panel datasets. Gong and Sickles (1992) conduct a Monte Carlo comparison of DEA and three types of SFAs. They use panel estimation methods and come to the conclusion that the choice of the functional form plays a key role in the estimation accuracy of firm-level inefficiencies. Inappropriate functional form can cause distorted efficiency measurement. Constant elasticity of substitution and translog (CES-TL) functional form proved to be the better performing one in almost every cases, and this model also outperforms DEA. Another important issue is the estimation method. Stochastic frontier function can be estimated using several panel approaches. The within panel estimator that allows correlation between individual fixed effect (i.e. inefficiency) and independent variables (i.e. inputs) generates good results even in the absence of these correlations (i.e. in the case of no endogeneity). Based on the simulations, the within estimator is preferred and it also outperforms DEA in many cases. Overall, SFA panel models do a good job in estimating the true inefficiency rates.

Ruggiero (2007) evaluates the performance of the SFA and DEA panel models and comes to the conclusion that in a panel setting, SFA outperforms the deterministic approaches. However, it is important to note that no misspecification was considered and

even in this setting, SFA models were not converging in many cases when the variance of the noise was relatively high.

4.2 PRODUCTION EFFICIENCY ANALYSES OF THE MEAT SUPPLY CHAIN

In this subsection we will review some prior efficiency analyses conducted in the meat supply chain. Animal breeding farms, processors and retailers will be considered, respectively. Focus is on the processing stage.

Iraizoz, Bardaji and Rapun (2005) analyze the Spanish beef livestock farms between 1989 and 1999. Their results show that the ratio of the produced and potential output is 0.84 indicating a significant level of inefficiencies. The estimation was made using translog production function and the expected value of inefficiency is explained with exogenous variables. This procedure makes it possible to identify the main reasons of inefficiencies and the effects of several measurements on inefficiency. For example, results show that the more debt a farmer has, the less effective his/her production is. It is also important and interesting that subsidies have a negative effect on efficiency.

Bezat-Jarzębowska and Rembisz (2013) analyze farm-level efficiency and competitiveness in the Polish agro-food sector. They estimate a translog and a Cobb–Douglas production function. Likelihood ratio test indicates that the more restrictive Cobb–Douglas form could not be rejected. The sum of the estimated parameters do not significantly differ from 1 which means that Polish farms use a constant return-to-scale technology. The average efficiency level is 0.76 (note that 1 means a fully efficient operation), i.e. output can be increased by 32% without using any additional inputs. However, efficiency scores strongly varies across farms indicating that there is a group of almost efficient and competitive farms and a (smaller) group that are operating very inefficiently.

Brümmer (2001) analyzes private farms in Slovenia using DEA and SFA methods. SFA is estimated assuming translog production function and the mean values of inefficiencies are explained by other variables. The average efficiency rate is equal to 0.74 and 0.44 using SFA and DEA, respectively. Constructing confidence intervals for the inefficiency rates shows that in many cases of the SFA estimations, the interval contains 1 therefore we cannot reject the hypothesis of fully efficient production. Those observations that have low efficiency scores also tend to have smaller confidence intervals. On the

contrary, the DEA case yields tighter confidence intervals, but it is due to its deterministic character.

Considering the Hungarian pig farms, Latruffe et al. (2013) investigate the production efficiency of 192 pig farms using the DEA approach. The research also addressed the question whether a stricter environmental regulation with regard to nitrate pollution will affect the level of pig production or not. The overall efficiency of the farms proved to be low (average is between 0.42 and 0.57), which means that there is space for improvement and pollution reduction as well. Latruffe et al. (2013) also explain the inefficiency scores with exogenous variables in a second stage quantile regression. Interestingly, farm characteristics proved to be insignificant in almost every quantile (except number of livestock units and utilized agricultural area), but regional variables (e.g. population, number of feed mills per pig farm in the region) do have significant effects.

The next stage of the supply chain is the processing stage. This is in the focus of the current paper, however, there is not much literature analyzing the production efficiency of this point of the supply chain. Bakucs et al. (2010) investigate whether Hungarian slaughterhouses and meat processors possess some market power in their input markets. In order to conduct this analysis, they estimate a structural model that is based on the profit maximization behavior of the firms. Firms' production function has a translog form. Bakucs et al. (2010) find that meat processors have slight market power in their input markets. The parameter estimates are in line with a regional Cournot competition of the processors which is believable, because of transportation barriers and costs. Bakucs et al. (2009) compare the Hungarian and the German meat processing sector with regard to market power towards their suppliers. The methodology they used is the same that was used by Bakucs et al. (2010). Results suggest that both German and Hungarian processors exhibit some kind of market power on pig breeders. However, this is tend to increase in Hungary and decrease in Germany.

The above mentioned two papers estimate the production function of the meat processors as a by-product and do not analyze the efficiency of the companies. This has not been possible to do, because Bakucs et al. (2009) and Bakucs et al. (2010) did not use firm-level data.

The aim of Kallas and Lambarraa (2010) was to determine the factors that drive market exit decisions in the Catalanian meat processing sector. In order to do this, they estimate firm-level inefficiencies as a potential driver for market exit. During the estimation procedure Kallas and Lambarraa (2010) use Cobb–Douglas production function and three

explanatory variables: labor expenses, costs of intermediate products and capital requirement of the production system. The estimated efficiency scores vary across the sample, there are firms with less than 0.3 and more than 0.9 as well. As it was expected, firms with smaller efficiency rates are more likely to leave the market.

Keramidou et al. (2013) estimate the production efficiency and profitability of 40 Greek meat processing companies using a two-stage DEA-based approach. In the first stage Keramidou et al. (2013) calculate technical inefficiency and in the second stage they assess the profit generating capacity of the firms. The results suggest that technical efficiency decreased between 1994 and 2007, and the profitability of the industry was also low. Interestingly, there is only small (and insignificant) correlation between efficiency and profitability. The most efficient firms were not able to achieve superior profitability which indicates some managerial inability. In average, a given firm in the Greek meat processing industry could have improved its performance by 25% to 38% depending on the year. Large producers tended to perform the best while medium sized firms performed the worst.

With the growing penetration of supermarkets and big retail chains, more and more consumers buy packaged and chilled meat products. O'Connor and Hammonds (1975) assess the efficiency of the centralized meat cutting and packaging systems, and compare it to carcass-handling systems. They come to the conclusion that centralized meat cutting and packaging is more technically efficient, but this efficiency can be still improved by lowering the usage of labor.

Finally, food retail sector is examined. Sellers-Rubio and Más-Ruiz (2009) focus on the Spanish food retail sector. They estimate stochastic frontier functions and explain the inefficiencies with other variables simultaneously. They use Cobb–Douglas production function and truncated normal distribution for inefficiencies. As a result, Sellers-Rubio and Más-Ruiz (2009) state that the overall efficiency of the Spanish supermarkets are high, however, there is some space to improve, 13.7% less resources (e.g. staff and wages) would have also been enough to reach the same output level (i.e. mean efficiency is 0.86).

Park and Davis (2011) conduct a productivity analysis in the US food retail market. They assume flexible model forms, translog production function and normal-gamma distribution for the inefficiency term. In general, supermarket efficiency proved to be high, 38% of the stores achieved more than 0.9, and the average efficiency is 0.86, the same as in Spain (Sellers-Rubio and Más-Ruiz, 2009). Additionally, Park and David (2011) find that employee trainings and part-time employment is able to increase store-level technical efficiency.

5 METHODOLOGY

In the previous section we have reviewed the two main types of production efficiency models, DEA and SFA. Monte Carlo simulations show that stochastic frontier analyses perform well, especially if we have a larger panel dataset. SFA often outperforms the deterministic models, therefore it is favorable to use stochastic approaches. However, real life validity of the assumptions have a crucial role in the analysis.

In this paper stochastic frontier analysis is used to obtain the inefficiency rates for the Hungarian meat processors. According to Lampe and Hilgers (2015) SFA is more widespread in economic research areas and it is especially popular in the field of agriculture. To overcome the obstacles of the methods, we give special attention to find the most appropriate assumptions based on previous researches and theoretical considerations.

5.1 THE BASIC IDEA OF STOCHASTIC FRONTIER ANALYSIS

Considering a particular firm operating in a given industry, the production frontier can be generally written as $\mathbf{q} = f(\mathbf{x}) - \mathbf{u}$, where $\mathbf{u}$ is a non-negative random variable that shows technical inefficiency. However, this is a strictly orthodox interpretation, because every nonzero deviation from the efficient production frontier is categorized as inefficiency. The main problem with this interpretation is that it is deterministic, there is no space for statistical noise that can arise from data measurement errors, market shocks or unfavorable weather conditions.

To deal with this problem, Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977) independently suggested the estimation of the stochastic frontier production function that has the form (in a panel setting):

$$\ln q_{it} = \mathbf{X}'_{it}\boldsymbol{\beta} + v_{it} - u_{it}, \quad (1)$$

where q_{it} is the output of firm i at time t , $\boldsymbol{\beta}$ is a vector of unknown parameters, v_{it} is symmetric (idiosyncratic) random error term and u_{it} represents the inefficiency of the given firm in the given time period. In this framework, one firm can produce only one output. However, this can be interpreted as the aggregate value of the outputs which allows the analysis of a multi-product company (such as almost every firm in the world). In this paper we will follow this approach.

Technical efficiency in this framework is given by

$$TE_{it} = \frac{q_{it}}{q_{it}^*} = \frac{\exp(\mathbf{X}_{it}'\boldsymbol{\beta} + v_{it} - u_{it})}{\exp(\mathbf{X}_{it}'\boldsymbol{\beta} + v_{it})} = \exp(-u_{it}), \quad (2)$$

where q_{it}^* is the potential output of firm i at time t . However, technical efficiency can, but does not have to vary across time periods in a panel framework. If technical inefficiency is time-invariant then $u_{it} = u_i, \forall t$.

5.2 MODEL SELECTION AND PARAMETER ESTIMATION

The estimation of equation (1) is more complicated than the estimation of a normal regression because of the compound error term. There are several models that were developed to deal with this issue.

In this paper we used two types of fixed effects models. First, the fixed effects stochastic frontier is estimated following the approach of Schmidt and Sickles (1984). This is a very simple panel approach that requires the estimation of equation (3).

$$q_{it} = \alpha_i + \mathbf{X}_{it}'\boldsymbol{\beta} + v_{it}, \quad i = 1, \dots, N, t = 1, \dots, T \quad (3)$$

The individual constant term in equation (3) can be divided into two parts, $\alpha_i = \alpha - u_i$, where α is the constant term of the technology and u_i represents firm-level inefficiency and therefore $u_i \geq 0$. We can calculate firm-level inefficiency by exploiting this latter inequality. If the cross-section sample size is large enough (i.e. $N \rightarrow \infty$), then the overall constant term can be estimated by $\hat{\alpha} = \max_i(\hat{\alpha}_i)$, where $\hat{\alpha}_i$ is the estimated intercept for the i th firm. This assumes that there is at least one fully efficient company in the sample. On the other hand, there is no need to a distribution assumption of the inefficiency term which is favorable. Reiff, Sugár and Surányi (2002) used this method to analyze the production efficiency of the Hungarian industry.

Fixed effects estimator is always consistent in panel setting, but inefficient if firm-specific characteristics do not correlate with right-hand side variables. Random effects model is consistent and efficient if there is no correlation between the fixed effects and the regressors, but it is inconsistent in the case of correlated fixed effects and regressors. A usually applied test for fixed versus random effects models is the Hausman test. The test compares the random effects parameters to the fixed effects parameters directly. The null hypothesis is that the preferred model is a random effects model and the alternative is that the fixed effects model is preferred.

The fixed effects stochastic frontier estimation assumes that inefficiency rates do not vary across time periods. This is plausible if T is small in the sample. However, the present dataset covers a 13-year-long period. It is very likely that firm-level efficiencies changed during this time. To deal with this problem, we also estimated the ‘true’ fixed effects model developed by Greene (2005a) and Greene (2005b).

‘True’ fixed effects model estimates the following equation:

$$q_{it} = \alpha_i + \mathbf{X}'_{it}\boldsymbol{\beta} - u_{it} + v_{it}, \quad i = 1, \dots, N, t = 1, \dots, T, \quad (4)$$

where α_i is individual constant term not containing inefficiency. Inefficiency is captured by u_{it} that is allowed to be different from period to period. Each individual constant term is estimated using T number of observations, therefore this method is appropriate to be appropriate only if the length of the panel is large enough. In our dataset $T = 13$ which is a sufficient length of panel to use this approach.

In this framework distribution assumptions are needed in order to compute the log likelihood function.

$$\begin{aligned} v_{it} &\sim iidN(0, \sigma_v^2) \\ u_{it} &\sim iidG(\lambda, 0) \\ corr(v_{it}, u_{it}) &= 0 \end{aligned}$$

These assumptions state that v_{it} is an independent and identically distributed idiosyncratic error term with normal distribution and u_{it} follows exponential distribution and it is also independent and identically distributed across observations. The two error terms are statistically independent from each other.

Firm-level inefficiency can be explained by exogenous variables. The most basic idea is to run a second stage regression where predicted inefficiency is the dependent variable. However, it was pointed out by Wang and Schmidt (2002) that this approach leads to biased estimates. The solution can be a one-step estimation when λ is modelled as being scaled using some exogenous variables, $\mathbf{z}_{it}$, formally, $u_{it} \sim iidG(\mathbf{z}'_{it}\boldsymbol{\delta}, 0)$. This approach is also favorable because in the presence of uncontrolled heterogeneity inefficiency estimates may be biased.

The estimation strategy is more complicated than it was in the previous case. This type of model was first estimated by Polachek and Yoon (1996) and adopted to production efficiency analysis by Greene (2005a). Initial parameter problem is crucial, therefore a

consistent initial estimation is important. The first step is to estimate the parameter vector, β , using simple fixed effects estimation. The firm-specific intercept can be calculated by $\hat{a}_i = \bar{q}_i - \bar{X}_i' \hat{\beta}$, where overbar refers to mean values. In the next step the full maximum likelihood function has to be maximized using the estimates as initial values. It will be an iterative process where Newton's method can be used. The process will terminate when convergence is achieved. These will be the estimated parameters of the model.

In order to obtain firm-specific inefficiency, we calculated the expected value of the inefficiency distribution given the observed output of firm i at time t (Jondrow et al., 1982).

$$E(u_{it}|q_{it}) = \sigma_v \left[\frac{\exp\left(-\left(\frac{q_{it}-x_{it}\beta}{\sigma_v\sigma_u}\right)-\frac{\sigma_v}{\sigma_u^2}\right)/\sigma_u}{1-\exp\left(-\left(\frac{q_{it}-x_{it}\beta}{\sigma_v\sigma_u}\right)-\frac{\sigma_v}{\sigma_u^2}\right)} - \left(\frac{q_{it}-x_{it}\beta}{\sigma_v\sigma_u}\right) - \frac{\sigma_v}{\sigma_u^2} \right], \quad (5)$$

where σ_v and σ_u are the standard deviations of the idiosyncratic and the inefficiency terms, respectively. Technical efficiency of the given firm at a given time is $\exp(-u_{it})$ as it was introduced at the beginning of this section (equation (2)). Industry-level efficiency is simply the mean of the firm-level efficiencies as the sample covers the industry fairly well.

Finally, there are several differences between the two applied models, but we want to highlight one important feature. Fixed effects model treat time-invariant firm-specific heterogeneity as inefficiency, because there is one common intercept for every firm and deviations from this intercept are labeled as inefficiency of the given firm. On the other hand, 'true' fixed effects estimator completely separates time-invariant firm-specific heterogeneity and inefficiency and treat time-invariant heterogeneity as not being inefficiency. Clearly, these are the two extremes that are possible in this framework. Estimating both of the models and comparing the estimated inefficiencies will define a lower and upper bound of inefficiency for every given firm.

5.3 FUNCTIONAL FORM

SFA is a parametric approach that requires the explicit determination of the production function. The most common functional forms are applied, translog and Cobb–Douglas production functions. Both of these functions are linear after logarithmic transformation. Translog production function is as follows (suppressing the firm and time subscripts):

$$\ln q = \alpha + \sum_{n=1}^N \beta_n \ln x_n + \frac{1}{2} \sum_{n=1}^N \sum_{m=1}^N \beta_{nm} \ln x_n \ln x_m, \quad (6)$$

where $n = 1, \dots, N$ is the number of inputs used for production. This is a very flexible functional form that also allows second-order approximation to an arbitrary production function. A restricted version of this function is the Cobb–Douglas production function where all the β_{nm} parameters are zero.

The principle of parsimony indicates that the simplest model should be chosen. Because the Cobb–Douglas model is nested in the translog model, we can use likelihood ratio test to test whether there is a significant difference between the two models or not. This method is commonly used in the literature (e.g. Reiff, Sugár and Surányi, 2002; Bezat-Jarzębowska and Rembisz, 2013).

6 DATA DESCRIPTION

Data used in estimation contains balance sheets and profit and loss statements for the Hungarian food industry from 2000 to 2012. From this database the financial information of the meat processing companies were selected. In order to do this, we used 4-digit NACE statistical classification of economic activities. Production, processing and preserving of meat and meat products category contains three subcategories. We used ‘Production and preserving of meat’ as well as ‘Production of meat and poultry meat products,’ but excluded ‘Production and preserving of poultry meat,’ since the focus of this study is to analyze the pig meat processors. The ‘Production and preserving of meat’ also includes slaughterhouse activity, but some processors have their own slaughterhouse thus these two phases (slaughtering and processing) may not separate. A better partitioning of the companies is not possible due to data availability. The database were collected by the National Tax and Customs Administration of Hungary and obtained from the Databank of the Research Centre for Economic and Regional Studies, Hungarian Academy of Sciences.

The annual datasets were combined into a panel. We wanted to analyze the same firms for a given period of time, therefore we selected such enterprises that were in the dataset every year. The panel used by Reiff, Sugár and Surányi (2002) was constructed the same way. Our balanced panel covers the period between 2000 and 2012. Some observations were dropped, because of unreliable data values (zero revenue or labor cost or tangible assets).

The dataset contains 94 companies. Bakucs et al. (2010) indicate that there are 100 companies on average in the Hungarian meat industry, which means that our panel can give a reliable picture about this industry.

The regional distribution of the firms is given in Figure 1. The distribution is approximately uniform, which indicates that the database represents well the geographic distribution of meat processors operating in Hungary.



Figure 1: Regional distribution of the firms in the sample (in 2012)

Source: own design based on National Tax and Customs Administration of Hungary dataset

It has to be taken into account that financial statements use current prices thus it is necessary to deflate them. We use the industrial producer price indices of the meat processing industry calculated by the Hungarian Central Statistical Office to deflate all the variables (except those that are expressed in naturals, e.g. number of employees).

We used two main types of variables to conduct this analysis. Production function estimation was carried out using Net sales revenue, Material-type expenditures, Payments to personnel and Tangible assets. On the other hand, efficiency measures were explained by Pre-tax profit or loss, Number of employees, and Domestic ownership dummy variable. Furthermore, we defined a new variable, called Value added, by subtracting Material-types expenditure from Net sales revenue. Table 2 shows a summary of these variables.

Table 2: Variables used for estimation and some descriptive statistics (financials are in thousand HUF)

Variable	Observation	Mean	Standard deviation
<i>Net sales revenue</i>	1,218	1,328,620	4,678,217
<i>Material-type expenditures</i>	1,220	1,153,066	4,088,351
<i>Value added</i>	1,218	173,678	692,443
<i>Payments to personnel</i>	1,220	115,615	486,095
<i>Tangible assets</i>	1,217	289,960	1,101,953
<i>Pre-tax profit</i>	1,222	14,554	279,869
<i>Number of employees</i>	1,220	71	254
<i>Domestic ownership (dummy)</i>	1,222	0.895	0.306

Notes: all variables are deflated

Source: National Tax and Customs Administration of Hungary, own calculations

Table 2 clearly shows that small companies dominate the sample, but there are some big players in this industry. Domestic ownership is dominant in the industry as it was mentioned earlier in Section 2. Figure 2 shows the distribution of the sample based on number of employees. The sample contains closely the same number of companies in the four smallest categories, but the number of firms is decreasing in the last three categories. However, it is quite common in every country that there are plenty of small factories and not so many large firms. The largest Hungarian meat processor had 2,708 employees in 2012.

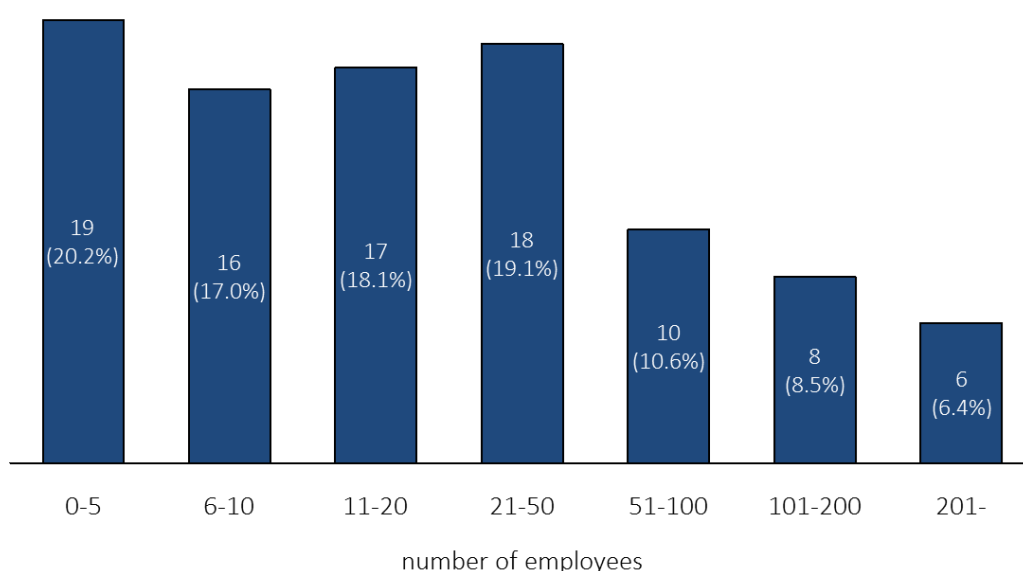


Figure 2: Distribution of the sample based on number of employees (2012)

Source: own design based on National Tax and Customs Administration of Hungary dataset

Finally, aggregate sales revenue and after-tax profit of the companies in the sample are visible in Figure 3. Compound average growth rate of deflated sales revenue was 2.7% in the sample period. This indicates that those companies survived the financial crisis expanded their production or more expensive products tended to get a bigger share in the product range of these companies. However, this expansion was not followed by an increasing profit level. After-tax profit of the companies were close to zero in almost every year.

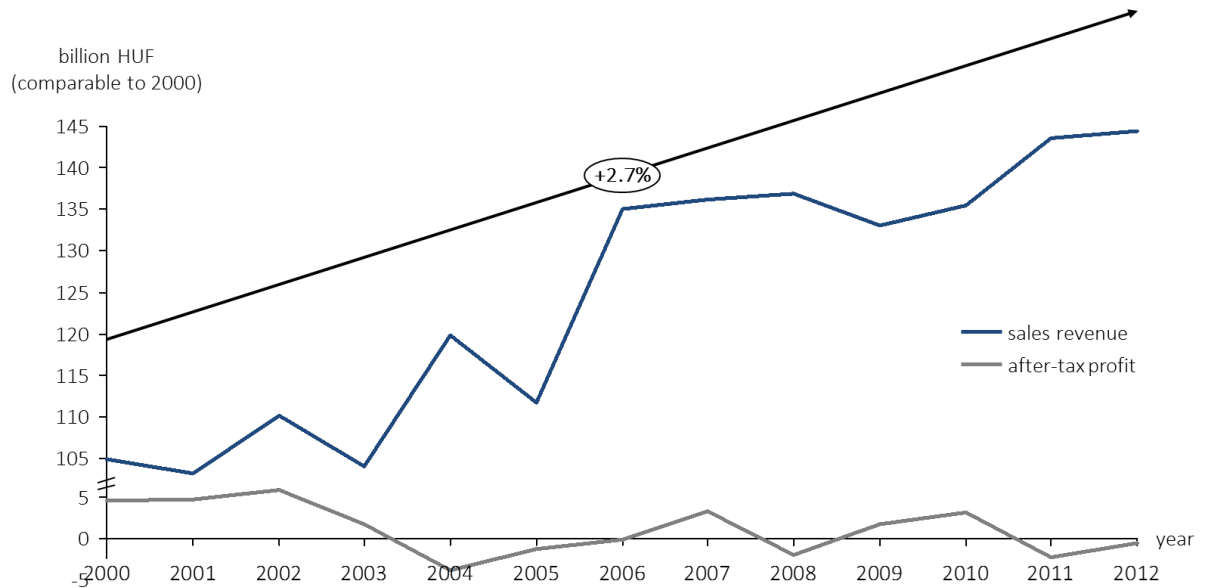


Figure 3: Aggregate sales revenue and after-tax profit in the sample

Source: own design based on National Tax and Customs Administration of Hungary dataset

7 RESULTS AND DISCUSSION

Estimations of stochastic frontier functions were conducted using Stata Statistics software. We applied `xtreg` and `sfp` commands (the latter developed by Belotti et al. (2012)) to estimate fixed effects and ‘true’ fixed effects models, respectively.

First, we will present the result of the traditional fixed effects estimation that will be followed by the results of the ‘true’ fixed effects estimation. Finally, the two result will be confronted.

7.1 RESULTS OF THE FIXED EFFECTS ESTIMATION

Fixed effects estimation was carried out using translog production function and value added as a dependent variable. Result are visible in Table 3.

**Table 3: Results of fixed effects stochastic frontier estimation
(dependent variable: $\ln(\text{value added})$)**

Variable	Coefficient	Std. error	t-statistics	p-value
$\ln(\text{payments to personnel})$	-0.049	0.0996	-0.49	0.626
$\ln(\text{tangible assets})$	0.347	0.1534	2.26	0.024
$\ln(\text{payments to personnel})^2$	0.055	0.0051	10.68	0.000
$\ln(\text{tangible assets})^2$	-0.003	0.0078	-0.43	0.666
$\ln(\text{payments to personnel}) \times \ln(\text{tangible assets})$	-0.020	0.0108	-1.88	0.060

Source: own estimation

We also estimated the same production function assuming randomly assigned firm-specific inefficiencies (i.e. random effects model). Hausman test indicates that the two parameter estimates are systematically different (p -value is 0.0347), i.e. firm-level inefficiency and explanatory variables seem to be correlated.

Despite the fact that there are some insignificant variables, likelihood ratio test rejects the null hypothesis of Cobb–Douglas production function with a p -value equals to 0.0000. Constant returns to scale were tested using F -statistics but the null hypothesis was rejected. The estimated production frontier is plotted in Figure 4.

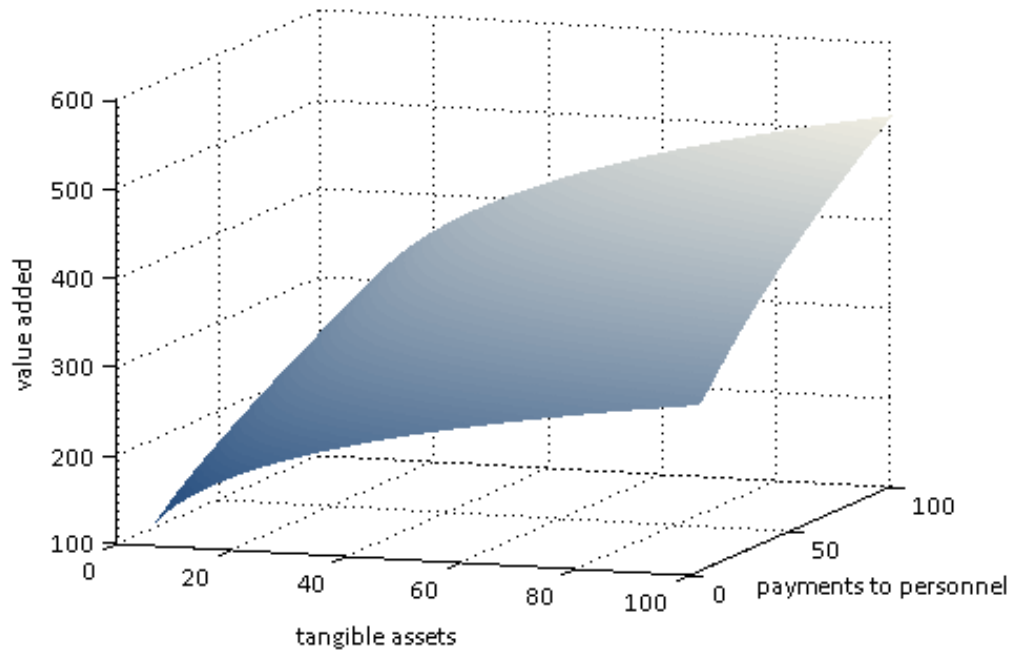


Figure 4: Production frontier estimation using fixed effects model

Source: own plot

In this framework, time-invariant production efficiency can be calculated using the method discussed above. Average production efficiency is really low, only 0.33 indicating that output can be tripled using the same quantity of inputs (i.e. labor and capital). The most efficient firm (having an efficiency level of 1 in this framework) is a relatively small company employing only 3-5 employees. However, the largest company based on headcount is also quite efficient with an efficiency score of 0.91. Figure 5 shows kernel density function of efficiencies. Results can be interpreted in two ways: There are many very inefficient companies in this industry or there are some firm specific effects that we failed to observe and therefore treated them as being inefficiencies.

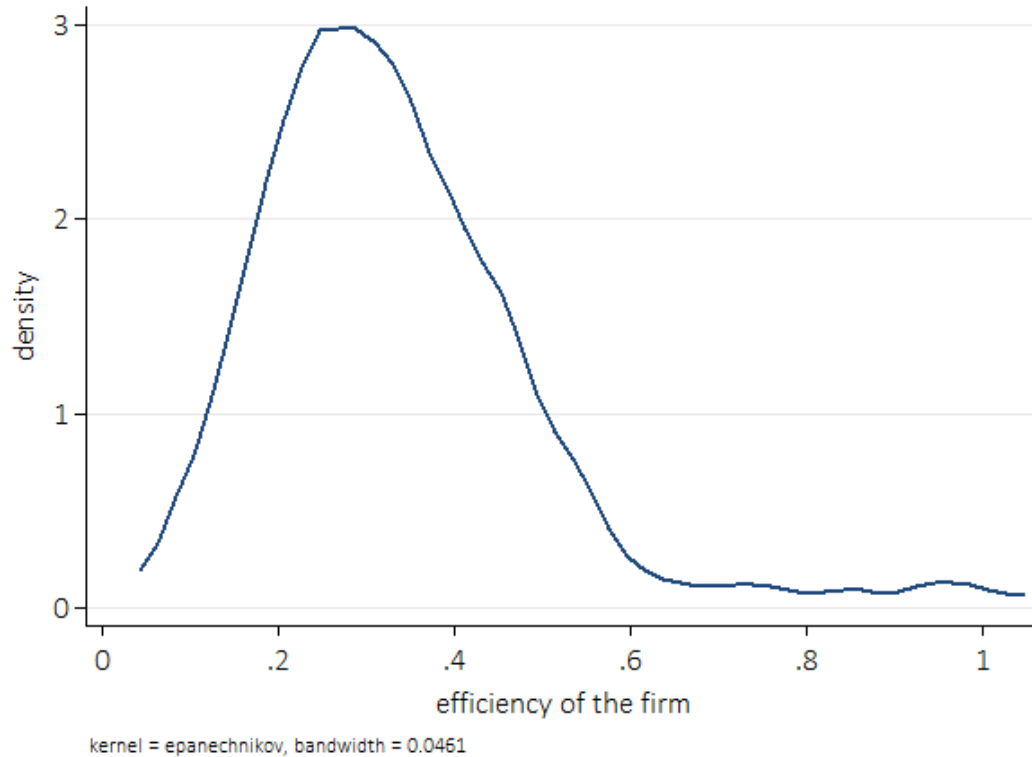


Figure 5: Kernel density estimation of firm specific efficiencies (fixed effects model)

Source: own plot

Note that those firms closed their factories or entered the market in the analyzed time period are not in the sample. It is very likely that these firms' efficiency were lower or higher, respectively. Low level of efficiency can be one important reason why they stopped operating and new entrants probably have better technology and therefore are able to produce more efficiently. Taking these effects into account, industry-level efficiency may be slightly biased, but this probably does not affect the overall conclusions of this analysis.

7.2 RESULTS OF THE 'TRUE' FIXED EFFECTS ESTIMATION

Fixed effects estimation yields time-invariant inefficiency scores. However, a 13-year-long period is long enough to execute some measurements in order to improve efficiency or efficiency can also decrease due to poor management or production decisions. In this subsection we carry out 'true' fixed effects estimation to calculate time-varying production efficiency. Hausman test carried out in the previous subsection indicates that fixed effects is the right model and random effects model leads to inconsistent estimations. Therefore in this subsection we employ the 'true' fixed effects estimator, not the 'true' random effects

one. ‘True’ fixed effects model was also estimated assuming translog production function. In order to account for technological change, the model also includes squared time trend.

In spite of the fixed effects model, the ‘true’ fixed effects model requires distribution assumptions for the inefficiency term. We used exponential distribution and the mean value and standard deviation (i.e. $1/\lambda$) was modelled as being dependent from Pre-tax profit, Domestic ownership dummy, Headcount and squared time trend. Table 4 contains the estimation results.

Table 4: Results of ‘true’ fixed effects stochastic frontier estimation

Variable	Coefficient	Std. error	z-statistics	p-value
<i>Stochastic frontier (dependent variable: $\ln(\text{value added})$)</i>				
$\ln(\text{payments to personnel})$	-0.077	0.0595	-1.29	0.196
$\ln(\text{tangible assets})$	0.301	0.1002	3.00	0.003
$\ln(\text{payments to personnel})^2$	0.053	0.0038	14.04	0.000
$\ln(\text{tangible assets})^2$	0.003	0.0045	0.63	0.529
$\ln(\text{payments to personnel}) \times \ln(\text{tangible assets})$	-0.024	0.0072	-3.32	0.001
t	-0.120	0.0165	-7.29	0.000
t^2	0.007	0.0011	6.21	0.000
<i>Mean and standard deviation of inefficiency distribution</i>				
<i>Pre-tax profit</i>	-7e-7	3.25e-7	-2.16	0.031
<i>D(domestic ownership)</i>	-0.348	0.2454	-1.42	0.157
<i>Number of employees</i>	-0.002	0.0009	-2.05	0.040
t	-0.485	0.0905	-5.36	0.000
t^2	0.031	0.0063	4.87	0.000
<i>Constant</i>	0.436	0.3578	1.22	0.223

Source: own estimation

Production function is similar to the previous case. However, time trend that should capture productivity changes shows that productivity decreased from year to year.

Firm-level efficiencies, as it was expected, show a completely different picture compare to the fixed effects model. Mean efficiency is 0.67, twice as much as in the previous case. Kernel density estimation of firm-level efficiencies is given in Figure 6.

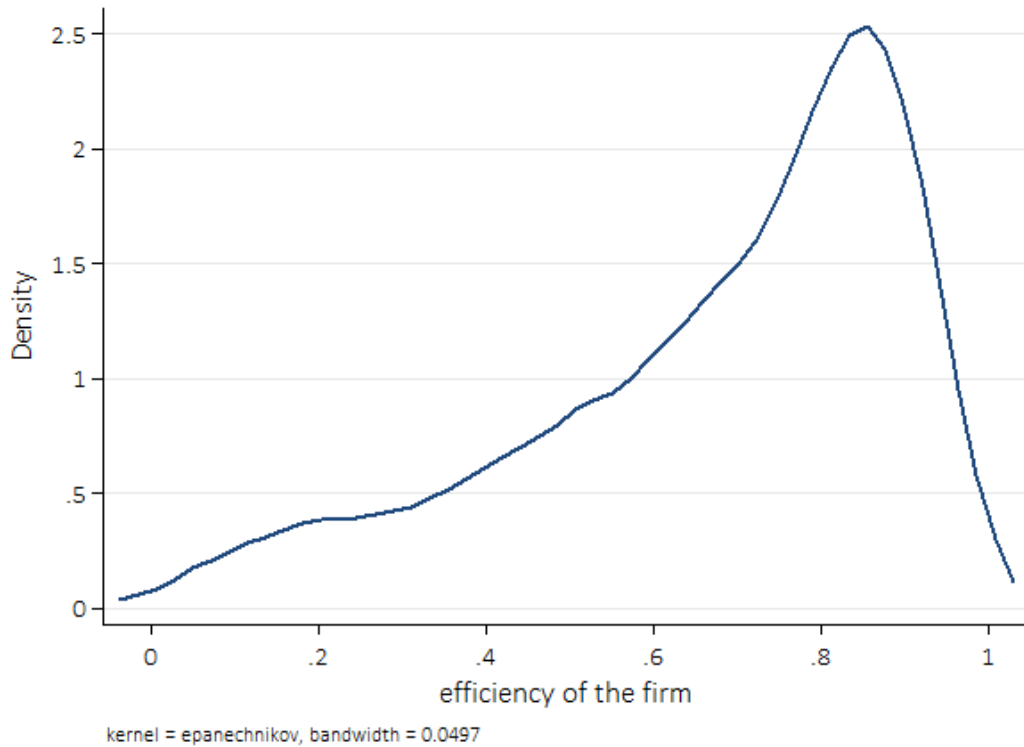


Figure 6: Kernel density estimation of firm specific efficiencies ('true' fixed effects model)

Source: own plot

It is important to analyze what drives firm-level efficiency. Mean value of inefficiency was explained using some explanatory variables. The second part of Table 4 contains the results. It is important to note that positive sign of a parameter indicates that the given variable increase inefficiency and negative sign indicates inefficiency reduction. According to Table 4, pre-tax profit, and number of employees decrease inefficiency. Larger firms tend to be *ceteris paribus* more efficient; and profitability and efficiency correlate positively, indicating that the more efficient a company is, the higher profit can it produce (*ceteris paribus*). Interestingly, domestic ownership is also associated with higher efficiency, however, this variable is not significant in 10% significance level either. The time trend of inefficiencies is plotted in Figure 7. It shows that efficiency was improved until 2007. However, the global economic crisis hit Hungary in 2008 had an unfavorable effect on firm-level efficiency. *Ceteris paribus* efficiency rate for a given company in 2012 was the same as in 2002.

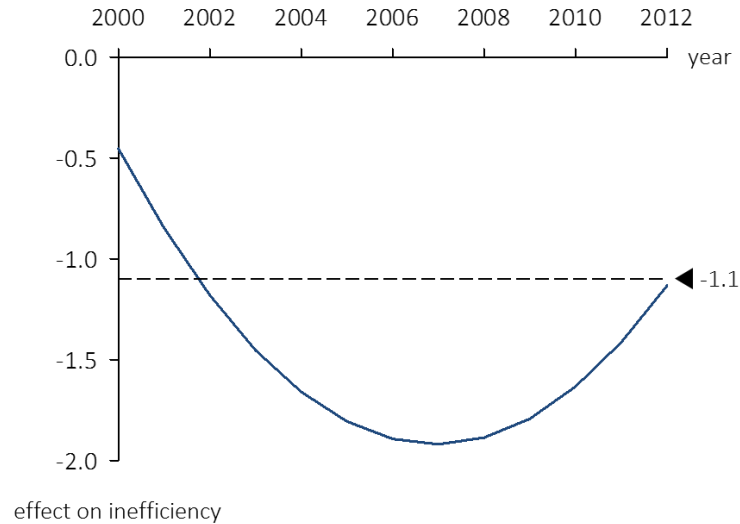


Figure 7: Time trend of mean inefficiencies

Source: own estimation

In order to compare efficiency rates obtained from fixed effects to ‘true’ fixed effects estimations, we calculated average efficiency rate as the mean value of firm-level efficiencies from 2000 to 2012. The correlation between the two efficiencies is really weak, only 0.198. Furthermore, only in 54% of the cases is time-invariant efficiency between the minimum and maximum value of time-varying efficiency, but there are only 6 (out of 94) companies where average time-varying efficiency is smaller than the time-invariant one.

To summarize the results, we can state that those are in line with our expectations, namely, there are some firm specific time-invariant effects. These effects may cause some inefficiencies, but are probably not completely inefficiencies. Therefore the two estimations applied in this research give an upper and a lower bound for firm-level efficiencies. This shows that the Hungarian meat processing industry struggles with some efficiency problems, there is space to improve that can have a result of lower input usage and therefore decreasing costs. However, Kallas and Lambarraa (2010) estimated an average efficiency of 0.53 for the Catalanian meat processors and Keramidou (2013) an average of 0.7 for Greek processors. It means that in average Greek companies operate more efficiently than the Hungarian ones, but this statement seems not to be true in the comparison with Catalanian companies.

8 CONCLUSION

This study investigates on the production efficiency of the Hungarian meat processing industry. Meat processors create a critical area of the Hungarian industry as many high-capacity meat processors went bankrupt or had serious financial problems between 2011 and 2013. In our previous analysis, we came to the conclusion that suppliers and buyers do not have significant market power in relation with meat processors. Therefore unfavorable market situation is not the reason for the bankruptcy of many meat processors.

In the current research, we estimated firm-level efficiencies and identified the relevant factors affecting those efficiencies. Results suggest that profitability and number of employees are influencing efficiency. The profitable a firm is, *ceteris paribus* the higher the production efficiency of the given firm is. This shows that those companies that produced losses in the past are probably less efficient than the competition.

As a guideline for policy design, it can be important to analyze the history of the firm. If the firm is a loss making one for a long time then it is likely that this company did not operate as efficiently as the competition did. The bail-out of such a company bears with the risk of softening budget constraints, i.e. the management of the firm can believe that government will give financial support for the company in the future, too.

In the case of financial support, we suggest that government should emphasize the importance of efficiency improvement and define some objective productivity KPIs (e.g. final product/labor) in order to monitor the progress made by the new management. If production efficiency is not getting improved, then it will not worth to finance the company in the future.

The main limitation of the research is that we used a balanced panel dataset (due to data availability problems) and therefore those companies finished or began their operation between 2000 and 2012 are not in the sample. Those firms abandoned their activity were probably less efficient than the competition, but it is likely that new entrants have better technology and therefore are able to produce more efficiently. The result of these two adverse effects is not known, but the estimation bias is probably not too large.

REFERENCES

Literature

- Aigner, D. – Lovell, C. A. K. – Schmidt, P. (1977): Formulation and Estimation of Stochastic Frontier Production Function Models. *Journal of Econometrics*, Vol. 6, p. 21–37.
- Bakucs, L. Z. – Fertő, I. (2005): Marketing Margins and Price Transmission on the Hungarian Pork Meat Market. *Agribusiness*, Vol. 21, No. 2, p. 273–286.
- Bakucs, L. Z. – Fertő, I. – Hockmann, H. – Perekhoznuk, O. (2009): Market power on the edge? An analysis of the German and Hungarian hog markets. *Agrarwirtschaft*, Vol. 58, Heft 8, p. 339–347.
- Bakucs, L. Z. – Fertő, I. – Hockmann, H. – Perekhoznuk, O. (2010): Estimating Oligopsony Power in the Hungarian Market for Slaughter Hogs. *Eastern European Economics*, Vol. 48, No. 1, p. 64–78.
- Banker, R. D. – Gadh, V. M. – Gorr, W. L. (1993): A Monte Carlo comparison of two production frontier estimation methods: Corrected ordinary least squares and data envelopment analysis. *European Journal of Operational Research*, Vol. 67, p. 332–343.
- Belotti, F. – Diadone, S. – Ilardi, G. – Atella, V. (2012): Stochastic frontier analysis using Stata. *The Stata Journal*, Vol. vv, No. ii, p. 1–39.
- Bezat-Jarzębowska, A. – Rembisz, W. (2013): Efficiency-Focused Economic Modeling of Competitiveness In The Agri-Food Sector. *Procedia - Social and Behavioral Sciences*, Vol. 81, p. 359–365.
- Brümmer, B. (2001): Estimating confidence intervals for technical efficiency: the case of private farms in Slovenia. *European Journal of Agricultural Economics*, Vol. 28, No. 3, p. 285–306.
- Coelli, T. C. – Rao, D. S. P. – O'Donnell, C. J. – Battese, G. E. (2005): *An Introduction to Efficiency and Productivity Analysis*. 2nd ed., Springer, New York.
- Czibik, Á. – Makó, Á. (2008): *Nagyméretű kiskereskedelmi üzletláncok és beszállítóik kapcsolatának oksági elemzése. (Causal analysis of the relationship of big retail chains and their suppliers.)* Hungarian Chamber of Commerce and Industry, Research Institute of Economics and Enterprises, Budapest.
- EC (2011): *Study on the Competitiveness of the European Meat Processing Industry*. European Commission, Luxembourg.
- Eurostat (2011): *Food: from farm to fork statistics*. Eurostat, Luxembourg.
- Gong, B.-H. – Sickles, R. C. (1992): Finite sample evidence on the performance of stochastic frontiers and data envelopment analysis using panel data. *Journal of Econometrics*, Vol. 51, p. 259–284.
- Greene, W. (2005a): Fixed and Random Effects in Stochastic Frontier Models. *Journal of Productivity Analysis*, Vol. 23, p. 7–32.

- Greene, W. (2005b): Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of Econometrics*, Vol. 126, p. 269–303.
- Iraizoz, B. – Bardaji, I. – Rapun, M. (2005): The Spanish beef sector in the 1990s: impact of the BSE crisis on efficiency and profitability. *Applied Economics*, Vol. 37, p. 473–484.
- Jondrow, J. – Lovell, C. A. K. – Materov, I. S. – Schmidt, P. (1982): On the Estimation of Technical Inefficiency in the Stochastic Frontier Production Function Model. *Journal of Econometrics*, Vol. 19, p. 233–238.
- Kallas, Z. – Lambarraa, F. (2010): Technical efficiency and firm exit in the wine and meat sector: Policy implications. *New Medit*, N. 2/2010, p. 25–31.
- Keramidou, I. – Mimis, A. – Fotinopoulou, A. – Tassis, C. D. (2013): Exploring the relationship between efficiency and profitability. *Benchmarking: An International Journal*, Vol. 20, No. 5, p. 647–660.
- Krüger, J. J. (2012): A Monte Carlo study of old and new frontier methods for efficiency measurement. *European Journal of Operational Research*, Vol. 222, p. 137–148.
- Lampe, H. W. – Hilgers, D. (2015): Trajectories of efficiency measurement: A bibliometric analysis of DEA and SFA. *European Journal of Operational Research*, Vol. 240, p. 1–21.
- Latruffe, L. – Desjeux, Y. – Bakucs, Z. – Fertő, I. – Fogarasi, J. (2013): Environmental Pressures and Technical Efficiency of Pig Farms in Hungary. *Managerial and Decision Economics*, Vol. 34, p. 409–416.
- Mas-Colell, A. – Whinston, M. D. – Green, J. R. (1995): *Microeconomic Theory*. Oxford University Press, New York-Oxford.
- Meeusen, W. – Van Den Broeck, J. (1977): Efficiency estimation from Cobb–Douglas production function with composed error. *International Economic Review*, Vol. 18, No. 2, p. 435–455.
- O'Connor, C. W. – Hammonds, T. M. (1975): Measurement of the Economic Efficiency of Central-Fabrication- versus Carcass-Meat-Handling Systems. *American Journal of Agricultural Economics*, Vol. 57, No. 4, p. 665–675.
- Park, T. A. – Davis, E. E. (2011): Productivity and efficiency impacts of human resources practices in food retailing. *Applied Economics*, Vol. 43, p. 4689–4697.
- Polachek, S. W. – Yoon, B. J. (1996): Panel Estimates of a Two-Tiered Earnings Frontier. *Journal of Applied Econometrics*, Vol. 11, p. 169–178.
- Rácz, T. (2012): A Gyulai Húskombinát végnapjai. Megbélyegző segítség. (The last days of Gyulai Húskombinát Plc. A condemned help.) *HVG*, Vol. XXXIV, No. 49, p. 74–76.
- Reiff, Á. – Sugár, A. – Surányi, É. (2002): Productive efficiency in the Hungarian industry. *Hungarian Statistical Review*, Vol. 80, Special No. 7, p. 45–74.
- Ruggiero, J. (1999): Efficiency estimation and error decomposition in the stochastic frontier model: A Monte Carlo analysis. *European Journal of Operational Research*, Vol. 115, p. 555–563.

- Ruggiero, J. (2007): A comparison of DEA and the stochastic frontier model using panel data. *International Transactions in Operational Research*, Vol. 14, p. 259–266.
- Schmidt, P. – Sickles, R. C. (1984): Production Frontiers and Panel Data. *Journal of Business & Economic Statistics*, Vol. 2, No. 2, p. 367–374.
- Sellers-Rubio, R. – Más-Ruiz, F. J. (2009): Technical efficiency in the retail food industry. The influence of inventory investment, wage levels, and age of the firm. *European Journal of Marketing*, Vol. 43, No. 5/6, p. 652–669.
- Wang, H.-J. – Schmidt, P. (2002): One-Step and Two-Step Estimation of the Effects of Exogenous Variables on Technical Efficiency Levels. *Journal of Productivity Analysis*, Vol. 18, p. 129–144.

Sources from the Internet

- Nielsen Hírvilág. Élelmiszer-nél nőtt a kereskedelmi márkák piaci részesedése... (Market share of private label products increased...) hu.nielsen.com/site/20110307.shtml (Accessed: October 20, 2014.)
- Nielsen Hírvilág. Tízből hat fogyasztó tartja fontosnak... (Six consumers from ten prefer...) hu.nielsen.com/site/20111109.shtml (Accessed: October 20, 2014.)

Databases

- Annual Profit and loss statement and Balance sheet data, 2000–2012. National Tax and Customs Administration of Hungary, Budapest.*
- Hungarian Competition Authority – Competition statistic database.
www.gvh.hu/gvh/versenykultura_kozpont/versenystatisztika (Accessed: September 14, 2014.)

* A NAV Társasági Adóbevallás adatok a NAV tulajdonát képezik. A használt adatokat az MTA KRTK Adatbankja dolgozta fel, a szerző azokat Bakucs L. Zoltán szakdolgozójaként használta.