Zombor Berezvai

Production Efficiency Analysis of the Hungarian Meat Processing Industry

This paper analyzes the performance of the Hungarian meat processing industry in the wake of the global financial crisis. Between 2011 and 2013 many high-capacity meat processors went bankrupt in Hungary. Possible reasons for that could be unfavorable market situation and inefficiency in production. In this paper, the latter hypothesis is examined. Two different types of production function estimation techniques are used to calculate firm-specific inefficiency estimates. Based on the estimation results, the lower bound of average firm-level efficiency is 0.50, while the upper bound is 0.88. Estimated firm-level inefficiencies are compared to the characteristics of the given firms. Pre-tax profit, company size and domestic ownership are associated with lesser inefficiency. On the other hand, time trend of inefficiencies indicate that the global financial crisis negatively affected the production efficiency of the meat processors. This can be a reason behind the bankruptcies happened.
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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 2012:74*). 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. Previous

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

price transmission analyses conducted in the Hungarian meat supply chain concluded that price transmission is symmetric and both input and output markets are competitive (*Bakucs–Fertő 2005*; *Bakucs et al. 2006*; *Berezvai 2014*).

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.

The structure of this paper is as follows. Section 2 focuses on previous studies. Sections 3 describes the theoretical framework of the analysis, the methodology and the dataset used. Section 4 is made up of the results and discussion. Concluding comments are presented in Section 5.

Literature Review

Production efficiency analysis has 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 models and assumptions for our analysis.

Comparison of Stochastic and Deterministic Production Efficiency Approaches

There are several methods estimating production efficiency. The two most widespread approaches are data envelopment analysis (DEA) and stochastic frontier analysis (SFA). The former one is a mathematical programing 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 an explicit production or cost function.

Comparing these two types of models, both of them have pros and cons. DEA is a rather deterministic approach that does not assume any measurement error, statistical noise or other random conditions. On the contrary, SFA can also be used if the data contains statistical disturbances. Real world data often contains 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 inefficiency term or the exact form of the production function, therefore this is a more robust approach compared to SFA.

Banker at al. (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.

Ruggiero (1999) also uses Monte Carlo simulations to compare the performance of stochastic and deterministic models. Surprisingly, he concludes 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).

A recent study of *Krüger (2012)* compares the estimation performance of the two "old" models (i.e. SFA and DEA) and a newer, non-parametric-stochastic model. *Krüger (2012)* uses Monte Carlo simulations 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 to 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 applied.

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–translog (CES-TL) functional form proved to be the best 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 are doing a good job in estimating the true inefficiency rates.

Ruggiero (2007) evaluates the performance of SFA and DEA panel models and concludes that in a panel setting, SFA outperforms the deterministic approach. However, it is important to note that no misspecification was considered and even in this setting, SFA models do not converge in many cases when the variance of the noise is relatively high.

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 et al. (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 (note that 1 means a fully efficient operation). 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 determinants 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. Result of the likelihood ratio test indicates that the more restrictive Cobb–Douglas form could not be rejected. The sum of the estimated parameters does not significantly differ from 1 which means that Polish farms use constant returns to scale technology. The average efficiency level is 0.76, 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 is 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 these intervals often contain 1, therefore one cannot reject the null hypothesis of fully efficient production. Those observations that have low efficiency scores also tend to have smaller confidence intervals.

Considering the Hungarian pig farms, *Latruffe et al. (2013)* investigate the production efficiency of 192 pig farms using the DEA approach. They examined 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. These indicate that production efficiency is not independent from market environment and the development of the related markets.

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 these companies. *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 that is believable due to 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. Results suggest that both German and Hungarian processors exhibit some sort 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)* is to determine the factors that drive market exit decisions in the Catalonian 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 input variables: labor expenses, costs of intermediate products and capital requirements 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. 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.

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 simultaneously explain the inefficiencies with other variables. They specify a Cobb–Douglas production function and inefficiencies are assumed to follow truncated normal distribution. 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 for improvement; 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 for 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–Más-Ruiz 2009*). Additionally, *Park and David (2011)* find that employee trainings and part-time employment are able to increase store-level technical efficiency.

Methodology and Data

Theoretical Framework

Production efficiency analysis has a strong microeconomic background. According to the theory of the 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 outputs from more than one inputs.

For a multiple-output production process, production technology describes the transformation. Let $S = \{(\mathbf{x}, \mathbf{q})\text{: } \mathbf{x} \text{ can produce } \mathbf{q}\}$ 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 opportunities.

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 it is only an intermediate product with zero net output. Using this notation, production efficiency is as follows (*Mas-Colell et al. 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 output using the same quantity of inputs or generates the same quantity of 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 for some $\mathbf{p} > \mathbf{0}$ price vector, then it is also efficient. The converse of this statement is also true, but only if Y (the production set) is convex. In this case, all the efficient technologies are also profit maximizing for some nonzero price vector.

However, this definition of efficiency covers only one aspect of efficiency, namely technical efficiency. Several other types of efficiencies could be taken into consideration (*Coelli et al. 2005*), but these are out of the scope of this paper.

The Basic Idea of Stochastic Frontier Analysis

As it was shown in the *Literature Review* section, Monte Carlo simulations indicate that stochastic frontier analyses perform well, especially if we have a large 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.

According to *Lampe and Hilgers (2015)*, SFA is more widespread in economic research areas and it is especially popular in the field of agriculture. Based on these considerations, stochastic frontier analysis is used to obtain the inefficiency scores for the Hungarian meat processors. To overcome the obstacles of the method, we put special attention to find the most appropriate assumptions based on prev ious researches and theoretical considerations.

Considering a particular firm operating in a given industry, the production function 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, etc.

To deal with this problem, *Aigner et al. (1977)* and *Meeusen and van den Broeck (1977)* independently suggest the estimation of stochastic frontier production functions that has the form (in a panel setting):

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

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 $u_{it} \geq 0$ 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 aggregate value of outputs that allows the analysis of multi-product companies (such as almost every firm in the world). In this paper, we will follow this approach.

Technical efficiency is given by

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

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

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 ($\nu_{it} - u_{it}$). Several models were developed to deal with this issue.

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

$$q_{it} = \alpha_i + \mathbf{X}_{it}^{'}\boldsymbol{\beta} + \nu_{it},\ i = 1, 2, \ldots, N;\ t = 1, 2, \ldots, T. \tag{3}$$

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 $u_i \geq 0$ has to hold. We can calculate firm-level inefficiency by exploiting this latter inequality. If the cross-section sample size is large enough (i.e. $N \to \infty$), 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 ith firm. This can be conducted if there is at least one fully efficient company in the sample. On the other hand, there is no need for any distributional assumption with regard to the inefficiency term. *Reiff et al. (2002)* use this method to analyze the production efficiency of the Hungarian economy (industrial sector).

Fixed effects estimator is always consistent in a 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 endogeneity. 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 the random effects model. In this case, the parameter estimation of the two models have to be statistically the same (deviations are not significant). If H_0 is rejected, then 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 altered 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:

$$q_{it} = \alpha_i + \mathbf{X}_{it}^{'}\boldsymbol{\beta} - u_{it} + v_{it},\ i = 1, 2, \ldots, N;\ t = 1, 2, \ldots, T, \tag{4}$$

where α_i is an individual constant term that is not treated as 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 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, the following distributional assumptions are needed to compute the likelihood function:

$$\begin{gathered} v_{it} \sim iidN(0,\ \sigma_v^2) \\ u_{it} \sim iidE(\lambda) \\ \operatorname{corr}(v_{it},\ u_{it}) = 0. \end{gathered} \tag{5}$$

These assumptions state that v_{it} is an independent and identically distributed idiosyncratic error term with normal distribution; u_{it} follows exponential distribution and it is also independent and identically distributed across observations. The two error terms are also 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 where λ is modelled as being scaled using some exogenous variables, $\mathbf{z}_{it}$, formally, $u_{it} \sim iidE(\mathbf{z}_{it}'\boldsymbol{\delta})$. In the presence of uncontrolled heterogeneity, inefficiency estimates may be biased. This approach helps to avoid this bias, too.

The estimation strategy was developed by *Polachek and Yoon (1996)* and used in 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, $\boldsymbol{\beta}$, using simple fixed effects estimation. Firm-specific intercepts can be calculated by $\hat{\boldsymbol{\alpha}}_i = \overline{\mathbf{q}}_i - \overline{\mathbf{X}}_{it}^{'}\hat{\boldsymbol{\beta}}$, 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 is used to achieve convergence. The process will terminate when convergence is achieved.

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

$$E(u_{it} \mid q_{it}) = \sigma_v \left[\frac{\exp\left(-\left(\dfrac{q_{it} - \mathbf{x}_{it}\boldsymbol{\beta}}{\sigma_v \sigma_u} \right) - \dfrac{\sigma_v}{\sigma_u^2} \right) \Big/ \sigma_u}{1 - \exp\left(-\left(\dfrac{q_{it} - \mathbf{x}_{it}\boldsymbol{\beta}}{\sigma_v \sigma_u} \right) - \dfrac{\sigma_v}{\sigma_u^2} \right)} - \left(\frac{q_{it} - \mathbf{x}_{it}\boldsymbol{\beta}}{\sigma_v \sigma_u} \right) - \frac{\sigma_v}{\sigma_u^2} \right], \tag{6}$$

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 in 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. The fixed effects model treat time-invariant firm-specific heterogeneity completely as inefficiency, because there is one common intercept for every firm. Deviations from this intercept are labeled as inefficiencies. On the other hand, the 'true' fixed effects estimator completely separates time-invariant firm-specific heterogeneity and inefficiency. Time-invariant heterogeneity is not treated as inefficiency. Clearly, these two extremes 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 (and for the meat processing industry as a whole).

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):

$$\ln q = \alpha + \sum_{n=1}^{N} \beta_n \ln x_n + \frac{1}{2} \sum_{n=1}^{N} \sum_{m=1}^{N} \beta_{nm} \ln x_n \ln x_m \ , \tag{7}$$

where $n = 1, 2, \ldots, N$ is the number of inputs used for production. This very flexible functional form 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 set to be zero.

Principle of parsimony indicates that the simplest model should be chosen. The Cobb–Douglas model is nested in the translog model, therefore we can use likelihood ratio test to test the joint significance of the β_{nm} parameters. This method is commonly used in the literature (e.g. *Reiff et al. 2002*; *Bezat-Jarzębowska–Rembisz 2013*).

Data

Data used for estimation purposes 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 filtered. In order to do this, we used 4-digit NACE statistical classification of economic activities, namely the companies grouped into 'Production and preserving of meat' as well as 'Production of meat and poultry meat products' based on their main activity. 'Production and preserving of poultry meat' is excluded from the sample, since the focus of this study is to analyze the pork meat processors. 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.

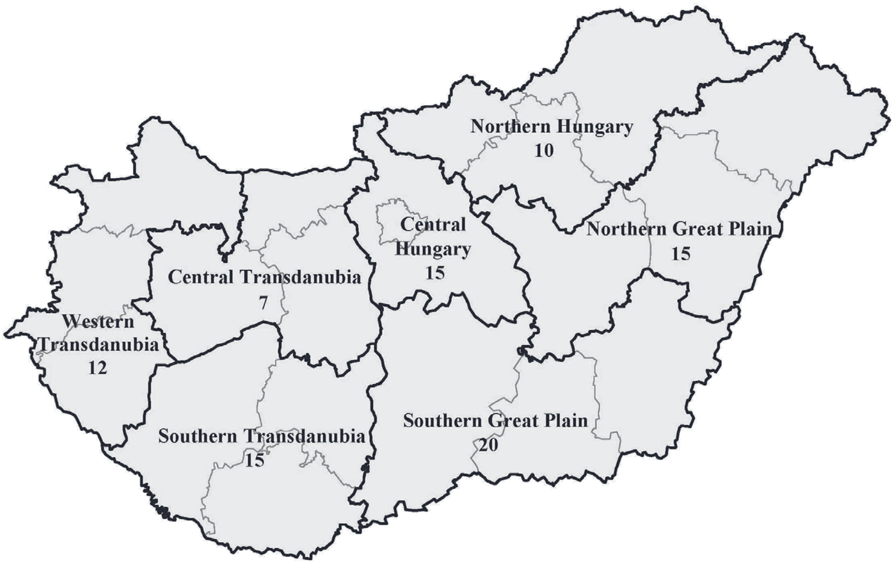
The annual datasets were combined into a balanced panel, i.e. we analyzed the same firms for a given period of time. The panel used by *Reiff et al. (2002)* was constructed the same way. Our balanced panel covers the time period between 2000 and 2012. Some observations were dropped, because of unreliable data values (zero revenue or labor cost or depreciation).

The final dataset contains 94 companies. *Bakucs et al. (2010)* indicate that there are 100 companies on average in the Hungarian meat processing 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 indicating that the database represents well the geographical distribution of the Hungarian meat processors.

Figure 1

Regional distribution of the firms in the sample



Source: based on the dataset collected by the National Tax and Customs Administration of Hungary

We used two main set of variables to conduct this analysis. Production function estimation was carried out using Net sales revenues, Material-type expenditures, Payments to personnel and Depreciation. On the other hand, efficiency measures were explained by Pre-tax profit or loss, as well as by Large company, and Domestic ownership dummy variables. Large company dummy is 1 if the company employs more than 100 people. Domestic ownership dummy is 1 if more than 50% of the issued capital is held by domestic owners, and 0 otherwise. *Table 1* shows a summary of these variables in 2000 and in 2012.

Table 1

Variables used for estimation and some descriptive statistics in 2000 and in 2012 (financials are in thousand HUF)

Variable	Mean	Standard deviation	Minimum	Maximum
Panel A. Year 2000				
Net sales revenues	1,139,732	4,251,223	4,968	37,731,279
Material-type expenditures	977,392	3,553,735	3,916	31,206,015
Payments to personnel	90,546	471,613	3	4,451,029
Depreciation	22,057	101,871	12	956,964
Pre-tax profit	54,181	385,596	-952,430	3,186,446
Large company (dummy)	0.10	0.30	0	1
Domestic ownership (dummy)	0.85	0.36	0	1
Panel B. Year 2012				
Net sales revenues	2,839,930	11,327,823	16	92,751,314
Material-type expenditures	2,523,846	10,442,258	1,508	89,354,469
Payments to personnel	217,162	854,406	447	7,996,999
Depreciation	43,965	163,615	31	1,495,759
Pre-tax profit	-7,749	281,310	-1,348,647	1,564,451
Large company (dummy)	0.15	0.36	0	1
Domestic ownership (dummy)	1	0	1	1

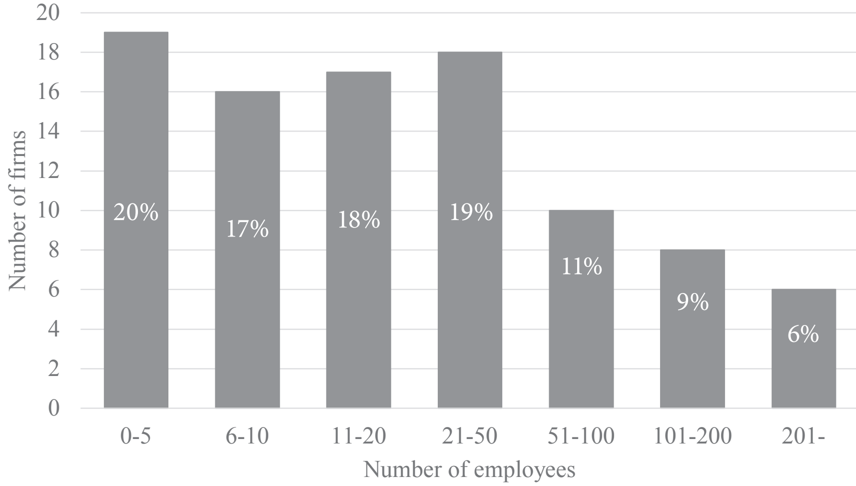
Notes: financials are in current prices
Source: own calculations based on the dataset collected by the National Tax and Customs Administration of Hungary

Table 1 clearly shows that small companies dominate the sample, but there are some big players in the industry. Domestic ownership is dominant.

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. This pattern is quite common in every industry. The largest Hungarian meat processor had 2,708 employees in 2012.

Figure 2

Distribution of the sample based on number of employees (2012)



Source: based on the dataset collected by the National Tax and Customs Administration of Hungary

Financial statements use current prices thus it is necessary to deflate them. We use different deflators for different data series. Revenues and pre-tax profits are deflated using industrial producer price index of meat processors, payments to personnel are deflated by the index of average gross earnings in the meat processing industry, depreciation is deflated by capital goods price index, and input prices are deflated using agricultural producer price index of pigs for slaughter. The Hungarian Central Statistical Office published all the price indices.

Using different deflators makes it possible to account for relative price changes occurred in the analyzed time period.

Results and Discussion

Estimations of stochastic frontier functions were conducted using Stata Statistics software. We applied the program developed by *Belotti et al. (2013)* for estimation purposes.

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.

Results of the Fixed Effects Estimation

Fixed effects estimation was carried out using translog production function and Net sales revenues as dependent variable. Result are visible in *Table 2*.

Table 2

Results of the fixed effects stochastic frontier estimation (dependent variable: ln(Net sales revenues))

Variable	Coefficient	Std. error	*p*-value
ln(Material-type expenditures)	1.890	0.105	0.000
ln(Payments to personnel)	-0.254	0.088	0.004
ln(Depreciation)	0.070	0.084	0.404
ln(Material-type expenditures)^2	-0.055	0.010	0.000
ln(Payments to personnel)^2	0.012	0.005	0.021
ln(Depreciation)^2	-0.015	0.006	0.023
ln(Depreciation) × ln(Material-type expenditures)	0.019	0.012	0.124
ln(Depreciation) × ln(Payments to personnel)	-0.008	0.010	0.441
ln(Payments to personnel) × ln(Material-type expenditures)	0.020	0.014	0.139

Source: own estimation

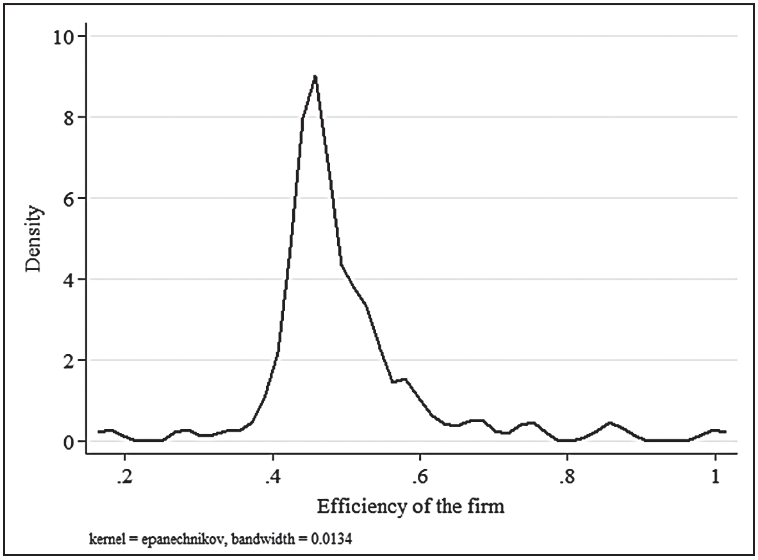
Gong and Sickles (1992) conclude that fixed effects estimation yields favorable results. However, being as accurate as possible, we also estimated the same production function assuming randomly assigned firm-specific inefficiencies (i.e. the random effects model). Hausman test indicates that the two parameter estimates are systematically different (*p*-value is 0.000), 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 0.000.

In this framework, time-invariant production efficiency can be calculated using the method discussed above. Average production efficiency is low, only 0.50, indicating that output can be doubled in average using the same quantity of inputs (i.e. labor, capital and raw materials). The most efficient firm (having an efficiency level of 1 in this framework) is a relatively small company. However, the largest company based on headcount has an efficiency score of 0.61 indicating that it is more efficient than the average. *Figure 3* shows the 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 we failed to observe and therefore treated them as being inefficiencies.

Figure 3

Kernel density estimation of firm-specific efficiencies (fixed effects model)



Source: own estimation

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.

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 or other variations. Thus, we calculated time-varying production efficiency by applying the 'true' fixed effects approach. This model was also estimated assuming translog production function. In order to account for technological change, the model also includes squared time trend.

The 'true' fixed effects model requires distributional assumptions for the inefficiency term. We use the exponential distribution function. Log variance (i.e. $\ln(1/\lambda^2)$), which is also the logarithm of the square of the mean of the distribution, was modelled as being dependent from Pre-tax profit or loss, Large company, and Domestic ownership dummies and squared time trend. *Table 3* contains the estimation results.

Table 3

Results of the 'true' fixed effects stochastic frontier estimation

Variable	Coefficient	Std. error	*p*-value
Panel A. Stochastic frontier (dependent variable: ln(Net sales revenues))			
ln(Material-type expenditures)	0.369	0.055	0.000
ln(Payments to personnel)	0.519	0.029	0.000
ln(Depreciation)	0.108	0.037	0.004
ln(Material-type expenditures)^2	0.060	0.004	0.000
ln(Payments to personnel)^2	0.067	0.003	0.000
ln(Depreciation)^2	0.017	0.003	0.000
ln(Depreciation) × ln(Material-type expenditures)	0.004	0.005	0.455
ln(Depreciation) × ln(Payments to personnel)	-0.042	0.004	0.000
ln(Payments to personnel) × ln(Material-type expenditures)	-0.109	0.007	0.000
t	-0.084	0.004	0.000
t^2	0.005	0.000	0.000
Panel B. Square of mean and variance of inefficiency distribution ($\ln(1/\lambda^2)$)			
Pre-tax profit	-4.35e-07	2.48e-07	0.080
D(Large company)	-0.985	0.231	0.000
D(Domestic ownership)	-1.524	0.209	0.000
t	-0.514	0.084	0.000
t^2	0.041	0.006	0.000
Constant	-1.347	0.337	0.000

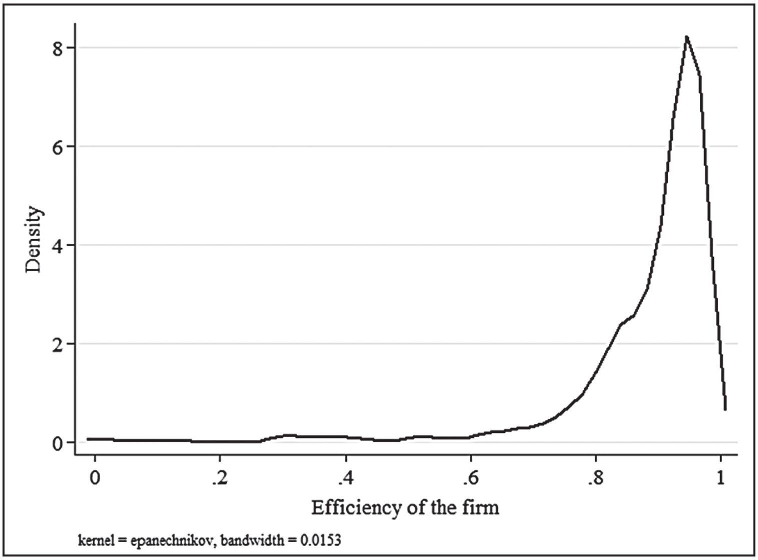
Source: own estimation

Results of the likelihood ratio test for the joint significance of the squared and interaction terms clearly indicate that translog function is the preferred one and rejects the null hypothesis of Cobb–Douglas production function (*p*-value is 0.000).

The mean value of firm-level efficiencies is 0.88. Kernel density estimation of firm-level efficiencies is given in *Figure 4*. Based on these figures, firm-level efficiencies are high in average, and there are only a few number of very inefficient firms. However, it is important to note that this procedure treats all time-invariant effects as firm-specific effects and not as inefficiencies. Indeed, it is more credible that at least a portion of these effects is inefficiency.

Figure 4

Kernel density estimation of firm-specific efficiencies ('true' fixed effects model)



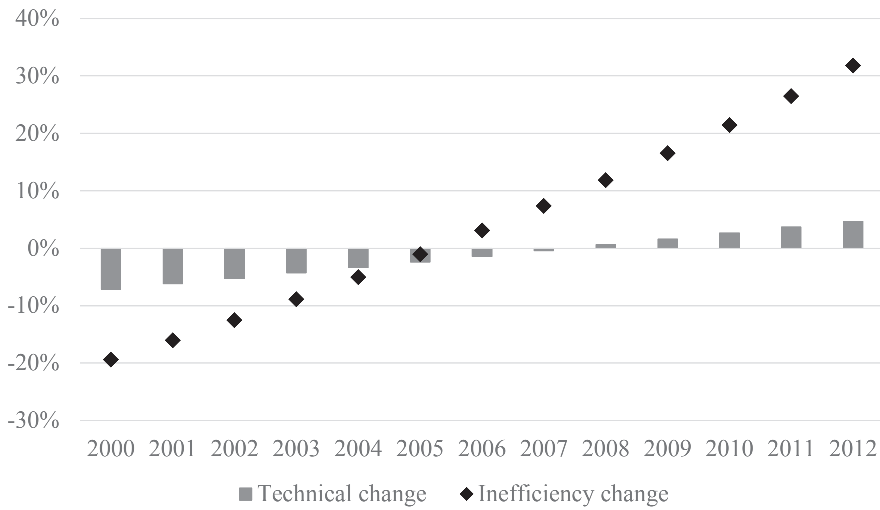
Source: own estimation

It is important to analyze what drives firm-level (in-)efficiencies. Mean value of inefficiency was explained using some explanatory variables. *Panel B* of *Table 3* contains the results. It is important to note that positive sign of a parameter indicates that the given variable increase (the mean value and the variance of) inefficiency and negative sign indicates inefficiency reduction. According to *Panel B* of *Table 3*, higher pre-tax profit *ceteris paribus* decreases inefficiency, i.e. profitability and efficiency correlate positively, indicating that the more efficient a company is the higher profit can it generate. This is in line with microeconomic theory, but contradicts the findings of *Keramidou et al. (2013)*. Larger firms also tend to be *ceteris paribus* more efficient. Interestingly, domestic ownership is also associated with *ceteris paribus* higher efficiency.

Besides these factors, time trend makes it possible to analyze the changes occurred in the 13-year-long time period. Both *Panel A* and *Panel B* of *Table 3* contain squared time trend. Time trend of *Panel A* shows technical changes. Positive sign indicates technology improvement, i.e. an upward shift in the production frontier, which means that all the companies are able to produce more output in period t compared to period $(t-1)$. *Figure 5* shows that this was negative until 2007, when it turned into a positive value. However, the potential output in 2012 is still significantly lower than it was in 2000. The high average efficiency showed earlier was calculated based on the worsening production frontier which makes that value less favorable.

Figure 5

Estimated annual change of mean inefficiency and technical change



Source: own estimation

Panel B of *Table 3* shows the time trend of the inefficiency distribution. While technical change is preferred to be positive; in this case, negative values are more favorable, because these show lower inefficiencies. The annual changes are also plotted in *Figure 5*. It shows that mean level of efficiency improved until 2005. Since 2006, mean efficiency descended year by year, and this trend continued during the global financial crisis. Between 2009 and 2012, mean inefficiency *ceteris paribus* increased by more than 20% annually. This is a colossal number and can be an important factor behind the bankruptcies happened.

Comparison of the Results

The fixed effects and the 'true' fixed effects models yielded different results in terms of efficiencies. This is meanly due to the different treatment of firm-specific heterogeneity. In the fixed effects model, inefficiency completely captures firm-specific heterogeneity, on the contrary, the 'true' fixed effects estimator separates these two factors entirely. It is likely that some portion of the firm-specific heterogeneity is inefficiency; therefore, the two models provided a lower and upper bound of efficiencies.

Based on the results, the average efficiency of the Hungarian meat processors is between 0.50 and 0.88. Compared to other EU countries, the results show that Hungarian meat processors are as efficient as their European peers are. The average efficiency of the Catalonian meat processors is 0.53 (*Kallas–Lambarraa 2010*) and the Greek companies achieved an average efficiency score of 0.70 (*Keramidou et al. 2013*).

Another important difference between the two models is that the 'true' fixed effects model allows efficiencies to alter in time. This provides therefore a more accurate estimation. Based on these considerations, we argue that real efficiencies are closer to the estimations of the 'true' fixed effects model, nevertheless, they have to be lower than those estimates.

To conclude, data indicates that the technical efficiency of the Hungarian meat processors is not lower than in other European countries or in other industries (e.g. retailing or farming). One problem can be the dynamics of the efficiencies that show a decreasing trend accelerated in the wake of the global financial crisis.

The global financial crisis hit Hungary in 2008 causing income reduction due to rising unemployment rate and increasing taxes. Meat consumption fell as well. Between 2007 and 2012, per capita pork meat consumption decreased by 11.2%. Gross output value of domestic manufacturers is also decreasing from 2007 onwards (even in nominal values). This shows that it also exists a substitution effect towards cheaper (and perhaps less profitable) products.

Due to these courses meat processors excess capacity have to have increased. This is in line with the findings of the production efficiency analysis, namely, that inefficiency *ceteris paribus* increased significantly after 2008 (*Figure 5*).

Decreasing efficiency and lower capacity utilization causes higher average cost[2] that negatively influences profitability and possibly causes heavy losses. After 2011, when demand reduction accelerated, many meat processors reached their shutdown point and went bankrupt.

This explanation is further supported by the fact that the largest meat processors have gone bankrupt. This is a reasonable assumption that these manufacturers had the highest fixed costs as well as they were the most affected by the continuous reduction in demand (smaller firms can easier find a market niche to maintain sales volume).

Conclusion

This study investigated the production efficiency of the Hungarian meat processing industry. Meat processors are an important part of the Hungarian industry, and between 2011 and 2013 many high-capacity meat processors went bankrupt or had serious financial problems.

We estimated firm-level efficiencies and identified the relevant factors affecting those efficiencies. Results suggest that profitability, domestic ownership and company size are the main determinants. The more profitable a firm is, *ceteris paribus* the higher the production efficiency of the given firm.

Unfortunately, a negative time trend is visible in average technical efficiency after 2006 that accelerated after 2008. One possible reason for that could be the reduction in pork meat consumption. This can be an important factor behind the bankruptcies in recent years. Therefore in case of financial support, we suggest that the government should lay emphasis on the importance of efficiency improvement and define some objective productivity KPIs in order to monitor the progress made by the new management. If production efficiency is not improving, then it will not be worth financing the company in the future.

The main limitation of the research is that we used a balanced panel dataset (due to data availability issues). Therefore, those companies finished or began their operation between 2000 and 2012 are not in the sample. Those firms which abandoned their activity were

[2] *If production volume decreases, only variable costs can be saved, fixed costs remain the same.*

probably less efficient than their competitors are, 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.

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