ANALYSIS OF THE HUNGARIAN ECONOMY

PRODUCTIVE EFFICIENCY IN THE HUNGARIAN INDUSTRY*

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The paper estimates industry-specific stochastic production frontiers for selected Hungarian manufacturing industries on a rich panel-data set between 1992–1998, then calculates firm-specific inefficiency estimates. One of the main findings is that between-industry differences in average inefficiency can be explained partially by differences in industry concentrations. Nevertheless, the within-industry differences are best explained by the presence of foreign owners, and also partially by the region of operation, but not by the exporting activity of the firms.

KEYWORDS. Stochastic production frontiers; Frontier estimation; Efficiency.

Measuring productivity and efficiency are very important when evaluating production units, the performance of different industries or that of a whole economy. It enables us to identify sources of efficiency and productivity differentials, which is essential to policies designed to improve performance.

The productivity of a production unit is defined as the ratio of its outputs to its inputs (both aggregated in some economically sensible way). Productivity varies due to differences in production technology, differences in the efficiency of the production process, and differences in the environment in which the production occurs. In this paper we are interested in isolating the efficiency component of productivity.

We define the efficiency of a production unit as the relation of the observed and optimal values of its inputs and outputs. The comparison can be a ratio of the observed to maximum possible output obtainable from the given set of inputs, or the ratio of the minimum possible amount of inputs to the observed required to produce the given output. (This is the widely used definition of technical efficiency.)

Until recently analyses have been facing difficulties when trying to determine empirically the potential production of a unit, and the productivity literature ignored the effi

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ciency component. Only with the development of a separate efficiency literature has the problem of determining productive potential seriously been addressed.

The measurement of technical efficiency is also important, as it enables us to quantify theoretically predicted differentials in efficiency. Examples include the theories connecting efficiency with market structure (see *Hicks*; 1935, *Alchian–Kessel*; 1962), models investigating the effects of ownership structure on performance (*Alchian*; 1965), and the area of economic regulation (for example, *Averch–Johnson* (1962) and *Bernstein–Feldman–Schinnar* (1990) examine the impact of economic environment and regulation on the efficiency of the firms). The paper is organized as follows. In the first part we provide theoretical backgrounds for our empirical calculations, from both economic and econometric points of view, while in the second part we analyze our data set, exploring the main characteristics of the firms in different branches of industry included in the sample. We also examine the time trends of these relevant variables, together with the representativity of our data set. The third part contains the estimates of the production function frontiers for different branches of the Hungarian industry. Our results about production functions also lets us draw some conclusions about different returns to scale in different industries. Next, in the fourth part we analyze sources of inefficiency differentials: the influence of export orientation, ownership structure and region of operation on the efficiency of the firms.

1. THEORETICAL BACKGROUNDS

This section presents the theoretical backgrounds for determining efficiency measures, and the details of our estimation technique.

Definitions and measures of productive efficiency

Productive efficiency has two components. The purely technical, or physical component refers to the ability to use the inputs of production effectively, by producing as much output as input usage allows, or by using as little input as output production allows. The allocative*,* or price component refers to the ability to combine inputs and outputs in optimal proportions in the light of prevailing prices. In this paper we only deal with the technical component of productive efficiency.

Koopmans (1951. p. 60) provided a formal definition of technical efficiency: 'a producer is technically efficient if an increase in any output requires a reduction in at least one other output or an increase in at least one input and if a reduction in any input requires an increase in at least one other input or a reduction in at least one output.' Thus a technically inefficient producer could produce the same outputs with less of at least one input, or could use the same inputs to produce more of at least one output.

Debreu (1951) and *Farrell* (1957) introduced a measure of technical efficiency. Their measure is defined as one minus the maximum equiproportionate reduction in all inputs that still allow continuous production of given outputs. Therefore, a score of unity indicates technical efficiency, a score less than unity indicates technical inefficiency. The conversion of the Debreu–Farrell measure (that is defined to inputs) to the output expansion case is straightforward.

Since our technical efficiency measurement is oriented towards output augmentation, we will examine them in that direction. Production technology can be represented with an output set:

$$L(x)=\{y: (x,y) \text{ is feasible}\}, \quad /1/$$

where x stands for inputs, and y for output(s). From this we can define the Debreu–Farrell output-oriented measure of technical efficiency:

$$DF_0\,(x,y) = max\ \{\theta: \theta y \in L(x)\}. \quad /2/$$

This concept will be used in this paper. We note that the Debreu–Farrell measure of technical efficiency does not coincide perfectly with Koopmans' definition of technical efficiency. Koopmans' definition requires that the point of production should belong to the efficient subset-part of a particular isoquant, while the Debreu–Farrell measure only requires that the production point should be on a particular isoquant. Consequently the Debreu–Farrell measure of technical efficiency is necessary, but not sufficient for Koopmans' technical efficiency. However, this problem disappears in many econometric analysis, in which the parametric form of the function used to represent production technology (e.g. Cobb–Douglas) ensures that isoquants and efficient subsets are identical.

The econometric approach to the measurement of productive efficiency: the theory of stochastic production function frontiers

The econometric measurement of productive efficiency is based on the well-known stochastic production function frontier approach of the efficiency analysis. The stochastic frontier production function, proposed independently by *Aigner, Lovell* and *Schmidt* (1977) and *Meeusen* and *van den Broeck* (1977), has been applied and modified in a number of studies later. The earlier studies involved the estimation of the parameters of the stochastic frontier production function and the mean technical efficiency of the firms in a given industry. It was initially claimed that technical inefficiencies for individual firms could not be predicted. But later *Jondrow et al.* (1982) presented two predictors for the firm effects of individual firms for cross-sectional data, and later panel data estimates were discovered as well.

To introduce the main idea, let us consider the well-known stochastic production function frontier approach of the efficiency analysis. In the most general setting (*Greene*; 1993) we assume a well-defined, smooth, continuous, continuously differentiable, quasi-concave production function, and we accept that producers are price-takers in their input-markets.

Our starting point is exactly the production function:

$$Q_i = f\left(\mathbf{x}_i;\boldsymbol{\beta}\right), \quad /3/$$

where Q denotes the somehow measured single output, $\mathbf{x}$ denotes the vector of inputs, $\boldsymbol{\beta}$ are parameters and i is used to index the firms.

In most applications, the specification of the function $f(\cdot)$ is either Cobb–Douglas or translog production function. These choices are mainly made for convenience, as either of these allows us to obtain linear equations in the parameters when taking the logarithm of /3/. Therefore if we introduce $y_i = \ln Q_i$, and from this point we denote by $\mathbf{x}_i$ the appropriately transformed input-vector of /3/, then we can write the logarithm of /3/ as:

$$y_i = \alpha + \boldsymbol{\beta}^T \mathbf{x}_i + \varepsilon_i \qquad /4/$$

$$\varepsilon_i = v_i - u_i . \qquad /5/$$

Here the ε_i residual term has two components: irregular events (like weather, unforeseen fluctuation in the quality of inputs etc.), and the firm's inefficient production.

The effect of irregular events is captured by the variable v_i,[4] and we assume that this can affect the actual production in either way; hence v_i can be both positive and negative. In particular, it is typical to assume that v_i is normally distributed with mean 0 and variance σ_v^2. This assumption will be used throughout the paper.

The effect of the firm's inefficient production is captured by term u_i. It is obvious that inefficiency negatively influences the production, that is why it has a negative sign in /5/. This means that the u_i variable itself is assumed to be non-negative.[5] As for the relation between the two parts of the compound error term, we will stick to the assumption (when applicable) that u_i is independent from v_i. The assumptions concerning u_i distinguish the different families of models from each other. We can list the following possibilities.

1. We can assume that u_i is constant for each observation (firm). This would mean that u_i is deterministic. However, these firm-specific constants can only be estimated if we have several observations for each firm. Therefore this approach (often called as fixed effects approach) can only be used for panel data.[6]

2. Alternatively, we can assume that u_i is stochastic, and the efficiency component of each unit can be characterized with the same probability distribution. With these assumptions, this approach can be used for both cross-sectional and panel data. (In case of panel data set, this is the random effects approach.)

If u_i is stochastic, there are other possible choices regarding to its distribution.

[4] One of the first attempts to estimate production frontiers was done by *Aigner* and *Chu* (1968), but they disregarded this irregular term; therefore they searched for the deterministic frontier of the production function. This method can be criticized from several aspects (see for example *Greene*; 1993), moreover it is only a special case of the general model introduced here (namely, when $\sigma_v = 0$). Therefore further we will not deal with this model.

[5] When first describing the stochastic frontier of the production functions, *Aigner, Lovell* and *Schmidt* (1977) defined $\varepsilon_i = v_i + u_i$, assuming in the same time that u_i is non-positive. Since then our notation became conventional.

[6] This is easy to see if we consider the following: if u_i is constant for all *i*, then adding it to the constant term of the regression we obtain the 'firm-specific' constant terms: one constant term for each firm (observation). This means as many parameters as many observations we have, therefore in cross-sectional data (when we have only one observation for each firm) the number of parameters to estimate would be higher than the number of observations.

a) We can assume: u_i is half-normally distributed, i.e. it follows a truncated normal distribution (truncated at 0), where the mean of the original normally distributed variable is 0.[7]

b) More generally, it is possible to assume that u_i follows a truncated normal distribution (where the mean of the original variable is μ, and truncation is made at 0).

c) It is also a usual assumption that u_i is exponentially distributed with parameter θ.

d) *Beckers* and *Hammond* (1987), and *Greene* (1990) consider the case when u_i follows a *gamma-distribution* with parameters $(\theta; P)$. This is the so-called gamma-normal model (the normal term reflecting to the normal distribution of v_i), and it can also be estimated, but it imposes so much numerical difficulties when computing the estimated parameters that it has been hardly used so far.

In the following, we will first present the estimators for the cross-sectional model, and then we generalize our results to panel data.

The cross-sectional model. We will insist on the assumption that the v_i variables are normally distributed, and its outcomes are independent. Furthermore, we saw previously that when we have a cross sectional model, we can only apply the approach of random effects. Therefore u_i must be stochastic: we assume that u_i follows a truncated normal distribution; the parameters of the underlying normal distribution are $\left(\mu; \sigma_u^2\right)$, and truncation is made at 0.

If we wish to determine the density function of our compound error term, $\varepsilon = v - u$, then we can use the well-known convolution rule (note that *u* and *v* are assumed to be independent):

$$f(\varepsilon) = \int_{-\infty}^{\infty} f_u(t) f_v(\varepsilon + t)\, dt =$$

$$= \frac{1}{\sqrt{\sigma_u^2 + \sigma_v^2}\,\Phi\left(\frac{\mu}{\sigma_u}\right)} \phi\left(\frac{\varepsilon + \mu}{\sigma_u}\right) \Phi\left(\frac{\mu\sigma_v}{\sigma_u\sqrt{\sigma_u^2 + \sigma_v^2}} - \frac{\varepsilon\sigma_u}{\sigma_v\sqrt{\sigma_u^2 + \sigma_v^2}}\right).$$

Here $\phi(.)$ is the distribution function, $\Phi(.)$ is the cumulative distribution function of a standard normally distributed variable.

At this point it is a convention in the literature to rewrite the parameters of the model in the following way: introduce $\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$ and $\lambda = \frac{\sigma_u}{\sigma_v}$, or equivalently, $\sigma_v = \frac{\sigma}{\sqrt{1+\lambda^2}}$, and $\sigma_u = \frac{\lambda\sigma}{\sqrt{1+\lambda^2}}$.

[7] An alternative definition for the half-normally distributed variable is the absolute value of a normally distributed variable with mean 0.

With these parameters

$$f(\varepsilon) = \frac{1}{\sigma\Phi\left(\frac{\mu\sqrt{1+\lambda^2}}{\lambda\sigma}\right)} \phi\left(\frac{\varepsilon+\mu}{\sigma}\right)\Phi\left(\frac{\mu}{\lambda\sigma}-\frac{\varepsilon\lambda}{\sigma}\right). \qquad /6/$$

From /6/ the log-likelihood function of model /4/ is /5/ is as follows:

$$\ln \ell(\alpha;\boldsymbol{\beta};\mu;\sigma;\lambda) = \sum_{i=1}^{N} \ln f(\varepsilon_i) = -N\ln\sigma -$$

$$-N\ln\Phi\left(\frac{\mu\sqrt{1+\lambda^2}}{\lambda\sigma}\right) - \frac{N}{2}\ln(2\pi) - \frac{1}{2\sigma^2}\sum_{i=1}^{N}(\varepsilon_i-\mu)^2 + \sum_{i=1}^{N}\ln\Phi\left(\frac{\mu}{\lambda\sigma}-\frac{\varepsilon_i\lambda}{\sigma}\right), \qquad /7/$$

where N denotes the size of our cross-sectional sample, and $\varepsilon_i = \alpha - \boldsymbol{\beta}^T\mathbf{x}_i - y_i$.

The maximum likelihood estimates of this model can be obtained by maximizing this expression. Having this result accomplished, we can compute the estimates of the ε_i -s; denoted by e_i. As *Jondrow et al.* (1982) show, we can infer u_i from the estimated ε_i. Their main idea is that it is possible to determine the conditional cumulative distribution function of u_i, under the condition that the estimated value of ε_i happens to be e_i:

$$F(u_i|e_i) = \Pr(u < u_i|e_i) = \frac{\int_0^{u_i} f_u(t)f_v(e_i+t)\,dt}{\int_0^{\infty} f_u(t)f_v(e_i+t)\,dt}. \qquad /8/$$

With this, the conditional density function and the conditional expected value of u_i can be written as:

$$E(u_i|e_i) = \int_0^{\infty} uf(u|e_i)\,du = \frac{\lambda\sigma}{1+\lambda^2}\left[\frac{\phi\left(\frac{\mu}{\lambda\sigma}-\frac{e_i\lambda}{\sigma}\right)}{\Phi\left(\frac{\mu}{\lambda\sigma}-\frac{e_i\lambda}{\sigma}\right)} + \frac{\mu}{\lambda\sigma} - \frac{e_i\lambda}{\sigma}\right]. \qquad /9/$$

Having the maximum likelihood estimates for the parameters, this can be computed for all *i*. As *Greene* (1993) notes, this estimator is unbiased, but inconsistent. (Inconsistent, because regardless of *N*, the variance of it remains non-zero.)

The panel model. Now we turn to the panel model, which can be formulated as

$$y_{it} = \alpha + \boldsymbol{\beta}^T\mathbf{x}_{it} + \varepsilon_{it}, \qquad /10/$$

$$\varepsilon_{it} = v_{it} - u_i. \qquad /11/$$

Here the variables have the same meaning as in equations /4/ and /5/, with the exception that t stands for the time index. We assume that for each firm i, we have T_i observations.[8]

According to /11/, the inefficiency component of any firm is constant over time. If we omitted this assumption, we would have to estimate each firm's inefficiency component for each period, which would lead us back to the cross-sectional case. Furthermore, this assumption is not unreasonable for our data set, where we have at most seven observations for each firm. As we saw earlier, we can choose among different assumptions regarding to u_i : it can be either deterministic (fixed effects approach) or stochastic (random effects approach). Now we turn to the analysis of these.

Case 1. Fixed effects model. If u_i is deterministic, we can rewrite our model in /10/ and /11/ in the following way:

$$y_{it} = \alpha + \boldsymbol{\beta}^T \mathbf{x}_{it} + v_{it} - u_i = \left(\alpha - u_i\right) + \boldsymbol{\beta}^T \mathbf{x}_{it} + v_{it} = \alpha_i + \boldsymbol{\beta}^T \mathbf{x}_{it} + v_{it} . \qquad /12/$$

We can represent therefore the fixed and non-stochastic inefficiency term with the constant term of the regression, obtaining firm-specific constant terms. This model is the usual fixed effects panel model, of which the estimation is well-known.

Once we have the estimates for the firm-specific constant terms, we can estimate the firm-specific inefficiency terms as well. As *Gabrielsen* (1975) and *Greene* (1980) showed , in equation /12/ the OLS-estimates for $\boldsymbol{\beta}$ are consistent, and $\hat{\alpha} = \max_i \hat{\alpha}_i$ is also a consistent estimator for the overall constant term.[9] Hence

$$\hat{u}_i = \hat{\alpha} - \hat{\alpha}_i = \max_i \hat{\alpha}_i - \hat{\alpha}_i \qquad /13/$$

can be used for the estimation of the firm-specific inefficiency terms. Therefore, we will have by construction at least one firm which is producing on its efficiency frontier, the rest being under it (i.e., having positive inefficiency measure). The advantages and disadvantages of this method are summarized by *Greene* (1993). The advantages are the following.

– Unlike to the random effects model, where the inefficiency term is a part of the error term in the regression and is assumed to be uncorrelated with the inputs in the regression, here it is included in the constant term and no such implicit (and unrealistic) assumption is needed.

– We do not have to assume normality; our parameter estimates (with the previous correction for the constant term) are consistent in N without assuming normality.

– The firm-specific inefficiency estimates are consistent in T_i.

The disadvantages are as follows.

– This method does not allow us to include time-invariant inputs (like capital usage) in the model, as this would be exactly multicollinear with the firm-specific (and also

[8] We will see in the following that it is unnecessary to assume that T_i is the same for all firms.

[9] In both cases, consistency is understood as consistency in N, but not as consistency in T.

time-invariant) inefficiency terms, as both of these are constants for each observations of the same unit. Furthermore, if we simply omit these inputs from our model, then the effect of these time-invariant inputs will appear in the inefficiency component. The solution can be a random effect model under such circumstances.

Case 2. Random effects model with truncated normal distribution. We again assume that v_{it} is normally distributed, u_i follows a truncated normal distribution, and each realizations of u and v are pair-wise independent. Furthermore, different realizations of v are independent also, and this is true for u as well.

When constructing the likelihood function, we have to consider that by /11/, the residual terms $\left(\varepsilon_{i1},\varepsilon_{i2},\ldots,\varepsilon_{iT_i}\right)$ are not independent from each other, while these residual vectors are independent for different i-s. So what have to be constructed is the joint probability distribution function for the parameter vectors $\left(\varepsilon_{i1},\varepsilon_{i2},\ldots,\varepsilon_{iT_i}\right)$, $i=1,2,\ldots,N$. As

$$\varepsilon_{i1}=v_{i1}-u_i,\varepsilon_{i2}=v_{i2}-u_i,\ldots,\varepsilon_{iT_i}=v_{iT_i}-u_i,$$

the convolution formula generalizes to:

$$f\left(\varepsilon_{i1},\varepsilon_{i2},\ldots,\varepsilon_{iT_i}\right)=\int_{-\infty}^{\infty} f_u(t)\,f_v\left(\varepsilon_{i1}+t\right)f_v\left(\varepsilon_{i2}+t\right)\ldots f_v\left(\varepsilon_{iT_i}+t\right)dt=$$

$$=\frac{1}{\Phi\left(\dfrac{\mu}{\sigma_u}\right)\sigma_u\sqrt{2\pi}}\frac{1}{\left(\sigma_v\sqrt{2\pi}\right)^{T_i}}\int_0^{\infty} e^{-\left(\frac{(t-\mu)^2}{2\sigma_u^2}+\frac{(\varepsilon_{i1}+t)^2+(\varepsilon_{i2}+t)^2+\ldots+\left(\varepsilon_{iT_i}+t\right)^2}{2\sigma_v^2}\right)}dt.$$

With a similar reparametrization as in the cross-sectional case,

$$f\left(\varepsilon_{i1},\varepsilon_{i2},\ldots,\varepsilon_{iT_i}\right)=$$

$$=\frac{\left(\dfrac{\sqrt{1+T_i\lambda^2}}{\sigma_i}\right)^{T_i-1} e^{-\frac{T_i\lambda^2}{2\sigma_i^2}\sum_{j=1}^{T_i}\left(\varepsilon_{ij}-\bar{\varepsilon}_i\right)^2}}{\sigma_i\Phi\left(\dfrac{\mu\sqrt{1+T_i\lambda^2}}{\lambda\sigma_i}\right)}\left[\prod_{j=1}^{T_i}\phi\left(\frac{\varepsilon_{ij}-\mu}{\sigma_i}\right)\right]\Phi\left(\frac{\mu}{\lambda\sigma_i}+\frac{\sum_{j=1}^{T_i}\varepsilon_{ij}\lambda}{\sigma_i}\right). \qquad /14/$$

(In the former equation, $\bar{\varepsilon}_i=\dfrac{1}{T_i}\sum_{j=1}^{T_i}\varepsilon_{ij},\lambda=\dfrac{\sigma_u}{\sigma_v},\sigma_i=\sqrt{\sigma_v^2+T_i\sigma_u^2}$.) From this the log-likelihood function and error terms e can easily be computed.

To obtain estimates for the firm-specific inefficiency parameters, the method to follow is exactly the same as it was before. Following the procedure by *Jondrow et. al* (1982), we can determine the conditional cumulative distribution function, the conditional distribution function, and the conditional expected value of u_i, under the condition of the observed *e*-s.

$$E\left(u_i \middle| e_{i1}, e_{i2}, \ldots, e_{iT_i}\right) = \frac{\lambda\sigma_i}{1+T_i\lambda^2}\left[\frac{\phi\left(\dfrac{\mu}{\lambda\sigma_i} - \dfrac{\sum_{j=1}^{T_i} e_{ij}\lambda}{\sigma_i}\right)}{\Phi\left(\dfrac{\mu}{\lambda\sigma_i} - \dfrac{\sum_{j=1}^{T_i} e_{ij}\lambda}{\sigma_i}\right)} + \frac{\mu}{\lambda\sigma_i} - \frac{\sum_{j=1}^{T_i} e_{ij}\lambda}{\sigma_i}\right]. \qquad /15/$$

A very important feature of this estimator is that if $T_i \to \infty$, then $E\left(u_i \middle| e_{i1}, e_{i2}, \ldots, e_{iT_i}\right) \to \overline{e_i}$, which converges to u_i as our maximum likelihood parameter estimates are consistent.

Finally, the consistency of our inefficiency term estimator in T_i is true for all estimation methods that estimate the model parameters consistently. So we do not have to use the maximum likelihood estimator, any method resulting consistent parameter estimates will be appropriate.

2. THE BASIC CHARACTERISTICS OF THE DATA SET

The data set contains information from the balance sheets and profit and loss accounts of non-financial, profit-oriented corporations between 1992 and 1998. (The 7-year average of the number of employees at the selected enterprises was at least 20.) We wanted to examine a panel data set in our study, i.e., we only selected enterprises which had the same code number in each of the seven years. This means that instead of the original 4–6000 companies we included only 1839 in our data set. Because of our use of the panel data our study is relevant for the whole manufacturing and energy sectors.

This sample of course does not represent all the double entry book keeping companies in Hungary, but it does describe enterprises which are solidly present in, and represent a significant portion of the Hungarian economy. In order to characterize the weight and structure of the sample, we collected data from all Hungarian double entry book keeping, non financial companies and compared these with the distribution of some of the key variables in our sample, but these figures are not presented in this paper.

In this study we define productivity by using the classic concept of the production function, i.e., we approach it from the point of view of the productivity of production in puts. For this reason, our most important variables are output, labour and capital. We operationalized each variable using several number of measures.

For the output variable, we use: net sales revenues and value added. *For the labour variable* we use payments to personnel; average number of employees and *for the capital variable*: tangible assets and depreciation.

In the case of productive efficiency we explored the most important factors which affect its variability. These are:

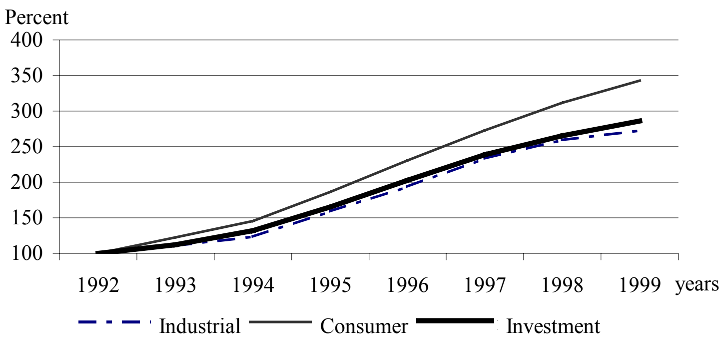
– region,
– type of economic activity (industrial classification),
– share of export activity,
– ownership of the enterprises.

We present the empirical information in two steps. First we analyze changes in the key variables of the double entry book keeping non financial companies between 1992 and 1998, and the productivity (absolute efficiency) of the companies in our sample and its variability. Secondly we use the stochastic production frontier method to analyze relative efficiency and the factors affecting it. Since there is a significant variability across industrial sectors we carried out the analysis for each sector separately. In order to ensure homogeneity within each group and at the same time to make sure that we have a sample large enough, we had to make some compromises.

Price changes between 1992 and 1998

Since most of our analyzed categories represent current prices it is necessary to deflate them using price indices. We gathered the producer price indices of each branch as well as the consumer and investment indices (see Figure 1).

Figure 1. Industrial, consumer and investment price indices
(Index: 1992=100)



As it is obvious from Figure 1, industrial and investment prices increased slower than consumer prices. In this paper we deflate the net sales revenue and the value added in each industry using its producer price index, the indicators of capital using the invest ment, and the value of personnel payments using the consumer price index. In the case of the volume index of the value added it would make sense to use the method of double deflation, but in Hungary input price indices are not calculated by industry (except in the agriculture). Therefore, we assumed that the companies suffered the same level of price increases from both the input and output side.

Time trends in output and ownership structure in the sample

In what follows we only analyze data from our sample of enterprises. First we explore changes over time in the key variables in each branch, focusing on input and output factors and the measures of labour and capital productivity. Before analyzing the factors of output and production, we present the ownership structures of the companies in our sample.

Table 1

The proportion of different types of equities by industries
(percent)

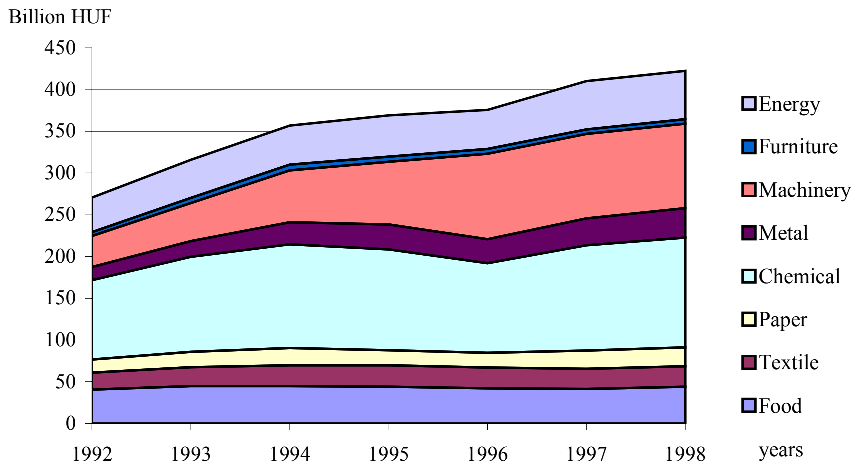
Industries	1992	1993	1994	1995	1996	1997	1998
	year						
				State owned			
Food	36.9	24.9	14.9	10.8	10	1.9	1.3
Textile	40.4	32.8	25.7	9.9	8.3	7.7	6.9
Paper	37	29.1	23	9.6	6.6	1.3	1.3
Chemical	77.1	71.9	61.9	43.1	28.1	16.8	12.1
Metal	40.9	20.6	15.4	15.6	13.2	4.7	4.5
Machinery	27.8	18	13.1	9.8	7.9	3.6	3.8
Furniture	35.3	20.6	16.8	8.9	8.2	3.4	3.3
Energy	93	90.1	88	68.7	61.3	53.1	48.1
Total	75.4	67.6	61.8	45.6	38	29.1	25.2
				Foreign owned			
Food	43.1	56.6	60.5	63.8	63.1	72.2	71.8
Textile	26.1	32.5	35.7	47.7	49.5	50.4	49.1
Paper	27.1	43.1	43.9	54.5	52.5	60.4	59.5
Chemical	14.4	19.8	25.6	43.1	53.6	60.9	63.3
Metal	24.2	34.7	36.8	38.1	47	59	60.1
Machinery	22.6	50.3	55.6	59.8	65.9	66.6	66.4
Furniture	18.6	29.3	32.2	34.7	35.8	36.4	36.7
Energy	0.4	0.6	0.6	20.9	27	30.3	41.3
Total	10.7	17.5	20.4	36.3	42.7	48.1	53.9

The proportion of state (and local government) ownership declined to its third, and by 1998 it represented a significant part only in the energy sector. Foreign ownership in our sample increased from 10 percent to over 50 percent by 1998. We can observe the highest rate in the food sector and the lowest in the furniture industry, but it exceeds one-third even here. The two indicators of output are the net sales revenues and the value added. Both indicators have been deflated by the producer price index of each branch so we analyze the output at 1992 constant prices.

The volume of output roughly doubled according to both indicators during the seven years. The value added increased a bit more rapidly and this is particularly true for the chemical and metal industries. In other words, the proportion of material requirements decreased in these sectors. The same is true for the energy sector but we have to take into account the fact that in the period under study prices were under state control in the energy sector and especially until 1995 the rise in retail prices remained well below that of the input, that is, the deflation of the value added using the producer price index overestimates its volume. After 1995 (and the privatization of the sector) cost based price setting was introduced so this problem is less significant.

Figure 2 displays the volume of the value added by industries. It is clear how the average increase in the share of metal and machinery industries raised their share in the overall output. The machinery industry produced only 14 percent of the value added in 1992, but 25 percent by 1998.

Figure 2. Value added at constant price in 1992–1998 by industries



Simple productivity indicators

Having characterized both output and inputs using two indicators, we will now describe the productivity of labour and capital using the following variables. For the productivity of labour: net sales/number of employees, value added/number of employees, net sales/payments to personnel, value added/payments to personnel. For the productivity of capital: net sales/depreciation, value added/depreciation, net sales/tangible assets, value added/tangible assets.

We calculated the changes in the size of these eight indicators at constant prices by industries, but in Table 2 we only present those that are based on value added.

The labour and capital requirements of the branches vary widely. Our indicators persuasively demonstrate that the textile and furniture industries are the most labour intensive ones, and the chemical and energy sectors are the least. During the seven years productivity increased most in the metal production and machinery industries. Examining time trends, the rate of increase seems relatively smaller (or the rate of decrease larger) comparing with personnel payments and with the size of the personnel. This indicates that the relative cost of labour increased even in real terms during the seven years under review.

Table 2

Value added indicators

Industries	1992	1993	1994	1995	1996	1997	1998	Index: 1992=100
	year							
	Value added/number of employees (thousand HUF/capita)							
Food	712.7	855	882.5	888.9	918	868.2	867.6	121.7
Textile	351.7	407.8	469.2	448	406.5	410.7	442.5	125.8
Paper	684	865.9	885.4	807.8	843	1049.1	1086.1	158.8
Chemical	1150.4	1550.2	1667.9	1668.4	1508.3	1790.2	1872.5	162.8
Metal	254.9	583.3	849.6	963.2	913.5	1009	1119.8	439.3
Machinery	423.9	563.5	803.2	939.5	835.3	1153.2	1117.2	263.6
Furniture	404.6	499.7	546.5	554.2	545.5	544.6	529	130.7
Energy	1187.7	1180.5	1116.1	1197	1175.9	1519.3	1641	138.2
Total	651.4	861.6	980	1012.3	930.5	1123.3	1160.4	178.1
	Value added/ payments to personnel (HUF/HUF)							
Food	1.8	1.7	1.7	1.7	1.8	1.7	1.6	88.9
Textile	1.3	1.2	1.4	1.5	1.5	1.3	1.4	107.7
Paper	1.4	1.4	1.5	1.5	1.6	1.9	1.9	135.7
Chemical	2.1	2.2	2.4	2.4	2.2	2.5	2.4	114.3
Metal	1.1	1.1	1.6	1.8	1.7	1.8	1.9	172.7
Machinery	0.9	1.1	1.5	1.8	2.3	2.3	2.1	233.3
Furniture	1.2	1.4	1.5	1.6	1.6	1.6	1.5	125
Energy	2.4	2	1.7	1.9	1.8	2.3	2.3	95.8
Total	1.6	1.6	1.8	1.9	2	2.1	2.1	131.3
	Value added/depreciation (HUF/HUF)							
Food	7.2	7.3	6.8	6.6	6.6	6.2	6.4	88.9
Textile	7.1	13.4	15.8	17.4	17.6	15.5	14.2	200
Paper	6.8	6.9	4.7	7.1	7.4	8.3	7.9	116.2
Chemical	2.5	3.4	4.1	4.9	5.2	5.6	5.9	236
Metal	4.9	5.4	8	8.8	8.6	9.3	9.2	187.8
Machinery	5.4	6.2	8.2	10	12.5	12.4	12.2	225.9
Furniture	10.4	12.9	14.1	13.8	14.5	13.7	13	125
Energy	1.9	2.6	3.1	3.1	2.5	3.3	3.5	184.2
Total	3.3	4.3	5.1	5.9	6.1	6.5	6.7	203
	Value added/tangible assets (HUF/HUF)							
Food	0.44	0.54	0.56	0.62	0.69	0.67	0.76	172.7
Textile	0.83	1.01	1.28	1.51	1.63	1.47	1.42	171.1
Paper	0.45	0.64	0.85	0.84	0.84	1.03	1.03	228.9
Chemical	0.26	0.38	0.49	0.56	0.56	0.69	0.69	265.4
Metal	0.35	0.47	0.74	0.92	0.92	0.98	1.1	314.3
Machinery	0.37	0.55	0.84	1.16	1.49	1.73	1.61	435.1
Furniture	0.62	0.96	1.11	1.27	1.35	1.45	1.43	230.6
Energy	0.1	0.14	0.16	0.21	0.24	0.34	0.36	360
Total	0.25	0.35	0.45	0.55	0.64	0.75	0.77	308

It is obvious that the productivity of capital is the lowest in the energy sector and in the chemical sector (that is, these are the most capital intensive branches). The dynamics of change over time, however, differs quite a bit according to the four indicators, although they all show significant (two- or threefold) increase. At the same time, we can observe some contradicting figures in some of the branches. In most sectors the size of output relative to the value of tangible assets increased more steep than relative to the depreciation. This means that the real value of tangible assets grew slower than the depreciation. Since we calculate the value of tangible assets for a given year by adding investments to its value in the previous year and deducting the depreciation this means that in most branches the value of new investments increased slower (or decreased faster) than the depreciation. Exceptional from this trend are textile and clothing industries with reverse situation.

We measured the productivity of both factors of production using four indicators of each. We analyzed the covariation of the variables (at the level of the enterprise) using principal component analysis. The four indicators of the productivity of labour move together relatively closely. The first principal component explains 62 percent of the variance.

The correlations between the first principal component and the variables are as follows: the net sales/number of employees is 0.62, the value added/number of employees is 0.79, the net sales/payments to personnel is 0.72 and the value added/payments to personnel is 0.81. On the basis of the previous we can approximate the common factor in the indicators of efficiency the best by using the value added/payments to personnel variable but the value added/number of employees variable is almost as good.

In the case of capital efficiency the first component explains 63 percent of the total variance. The correlation coefficients of the variables and the factor are: the net sales/depreciation is 0.77, the value added/depreciation is 0.82, the net sales/tangible assets is 0.64 and the value added/tangible assets is 0.70. In this case the variable value added/depreciation is the most useful one.

Obviously, the differences in productivity and the factors determining them can not be described very precisely by using these very simple descriptive statistics, therefore in the following we will employ more sophisticated statistical methods.

3. ESTIMATING THE INDUSTRY-SPECIFIC PRODUCTION FRONTIERS AND THE FIRM-SPECIFIC INEFFICIENCIES

In this part we describe how we chose the functional form for the production function and the variables to measure output, labour and capital input, how we estimated the parameters of the production function frontiers, calculated the firm-specific inefficiencies, transformed the data prior to estimation, and the effects of this if any. At last we would interpret the results obtained in this part.

The choice of production function

We assumed that in each industry there is an industry-specific, Cobb–Douglas type production function frontier of the following form:

$$y_{it}^{*} = \alpha_0 + \alpha_1 l_{it} + \alpha_2 k_{it} + v_{it} \, .$$

Here $\alpha = (\alpha_0, \alpha_1, \alpha_2)$ denotes the industry-specific parameters of the production function, y_{it}^*, l_{it}, k_{it} are the logs of the appropriately measured efficient output, labour input and capital input variables for firm *i* at time *t*, and finally v_{it} is the random disturbance term affecting firm *i*'s efficient output at time *t*. (The distribution of v_{it} is assumed to be normal).

The actual output of firm *i* at time *t* equals its efficient output y_{it}^* minus the firm-specific inefficiency, $u_i \geq 0$:

$$y_{it} = y_{it}^* - u_i = \alpha_0 + \alpha_1 l_{it} + \alpha_2 k_{it} + v_{it} - u_i \,. \qquad /16/$$

An alternative assumption could have been that the production function frontier is of translog-type (see, for example *Greene*; 1997). In this case the production function is the following:

$$y_{it}^* = \alpha_0 + \alpha_1 l_{it} + \alpha_2 k_{it} + \alpha_3 l_{it}^2 + \alpha_4 k_{it}^2 + \alpha_5 l_{it} k_{it} + v_{it} \,. \qquad /17/$$

It is obvious that this contains the Cobb–Douglas production function as a special case (when $\alpha_3 = \alpha_4 = \alpha_5 = 0$), and the relevancy of the Cobb–Douglas model can be tested.

Indeed, we prepared estimates with this formulation as well for selected industries (containing the most influential machinery), and the results were as follows. The new parameters were jointly significant, indicating that the Cobb–Douglas type production function frontier may not be appropriate; however, the estimated firm-specific inefficiencies remained practically the same in the two cases (with a correlation coefficient above 0.98). Therefore, for the sake of simplicity of exposition, we decided to present the results obtained with Cobb–Douglas production function. We note, however, that obtaining the full set of results with the more flexible translog production function formulation remains for future research (affecting mainly the production function estimates, not the firm-specific inefficiency estimates).

The choice of variables

For each variable (output, labour, capital) we had two possible choices:

– for output, we used either total sales revenues (in what follows, simply revenues) or value added;
– for labour input, we used either wage costs or the number of employees;
– for capital input, we used either depreciation or tangible assets.

This gave us eight possibilities for the formulation of our model, summarized in Table 3. We estimated each possible model, to see whether the extent of the estimated parameters are sensitive to changes in the input variables. A detailed comparison of the results will be provided later.

Table 3

Variables in different models

Model	LHS variable	RHS variables	
		labour	capital
Model 1	Revenue	Wage cost	Depreciation
Model 2	Revenue	Wage cost	Capital
Model 3	Revenue	Number of employees	Depreciation
Model 4	Revenue	Number of employees	Capital
Model 5	Value added	Wage cost	Depreciation
Model 6	Value added	Wage cost	Capital
Model 7	Value added	Number of employees	Depreciation
Model 8	Value added	Number of employees	Capital

However, we should add at this point some theoretical consideration concerning the choice of the variables. For the output, our preferred variable is value added, since revenues can be pumped up by simply buying materials and then reselling them, without any real activity. On the other hand, value added can be negative,[10] which is hard to interpret (and makes estimation impossible because of the need to take the log of the variables).

For the labour input, we could not choose any of the two candidate variables only on theoretical grounds. The number of employees has the advantage of being a real measure, and does not require any discounting. Furthermore, it does not make any difference between different qualities of labour, and does not incorporate any changes in productivity of labour force, which played a significant role in the period under investigation. These shortcomings are at least partially resolved in the wage cost variable, which should be correlated to the productivity of the labour. However, an appropriate discount rate should be found to make the variables at different time comparable. In any case, these two variables are not the same, as one of them represents effective labour, while the other one does not. We will see what differences arise at the final results due to this effect.

Finally, we face the most difficult problem when trying to estimate the capital usage, as we do not have reliable variables for this one. We have the intangible assets, which is a stock variable, clearly insufficient to represent the current capital usage (which is a flow). Moreover, this measure of capital can change very quickly (when any investment is activated), and then experience does not change at all during several time periods (when despite the investment activity nothing is activated). An alternative way of measuring current capital usage is the use of depreciation. Admitting that the reported values of this can be influenced by taxing considerations, and are therefore also inappropriate to some extent, we still believe that this is more closely correlated to the capital input than the former asset variable.

Estimation of the parameters of the production function frontier

As we have only seven years of data (t=1992, 1993, …, 1998), we assumed that the firm-specific inefficiency (u_i) is constant over time. Moreover, we assumed that it is

[10] In our data set, only a small proportion of the observations have negative value added.

stochastic, with a half-normal distribution among firms in each industry. Finally, we also assumed that the inefficiency components are independent from the v_{it} random shocks affecting the stochastic production frontier.

Under these assumptions the parameters of the model can consistently be estimated by the random-effects panel model, described previously. Here we repeat the exact formulation of the model to be estimated (for each industry separately):

$$y_{it} = \alpha_0 + \alpha_1 l_{it} + \alpha_2 k_{it} + v_{it} - u_i \,. \qquad /18/$$

A technical note is appropriate here: in /18/, the expected value of the compound disturbance term $\varepsilon_{it} = v_{it} - u_i$ is non-zero, as $u_i \geq 0$, and therefore $E(u_i) > 0$. But consider:

$$y_{it} = \left[\alpha_0 - E(u_i)\right] + \alpha_1 l_{it} + \alpha_2 k_{it} + v_{it} - \left[u_i - E(u_i)\right], \qquad /19/$$

the same model with a disturbance variable of zero expected value. The standard estimated random-effects model parameters will be the parameters of this latter model, so, to obtain the parameters of our original model, we will have to add $E(u_i) = \sqrt{\frac{2}{\pi}}\sigma_u$ to the estimated constant parameter. [11] The random-effects estimates of the parameters of the labour and capital variables (α_1, α_2) are consistent estimates of the true parameters in the initial model.

4. ESTIMATION OF THE FIRM-SPECIFIC INEFFICIENCIES

With consistent estimates of the parameters of the previous model in hand,[12] we can prepare estimates of the compound disturbance terms in model /19/:

$$\hat{e}_{it} = \left(v_{it} - u_i + E(u_i)\right) = y_{it} - \left(\hat{\alpha}_0 - E(u_i) + \hat{\alpha}_1 l_{it} + \hat{\alpha}_2 k_{it}\right). \qquad /20/$$

If we subtract $E(u_i)$ from these estimates, we obtain estimates for the disturbance terms of our original model:

$$e_{it} = \hat{e}_{it} - E(u_i) = \left(v_{it} - u_i\right) = y_{it} - \left(\hat{\alpha}_0 - E(u_i) + \hat{\alpha}_1 l_{it} + \hat{\alpha}_2 k_{it}\right) - E(u_i)\,. \qquad /21/$$

As demonstrated previously, the estimates of the firm-specific inefficiencies can be obtained by using the formula defined by *Jondrow et al.* (1982) (see /15/ with $\mu = 0$).

With given observations $e_{it}, t = 1,\ldots,T_i$, and given estimates for σ_u and σ_v, we can calculate the conditional expected value of the firm-specific inefficiencies according to /15/. These will be consistent estimates of the true u_i -s.[13]

[11] This formula comes from the assumption that *u*-s are half-normally distributed among the firms in each industry.
[12] We made all calculations by LIMDEP; the program code was written by the authors, and available upon request.
[13] As in our data set the maximum value of *T* is 7, this is only of theoretical interest here.

Initial data manipulations

The initial transformations that we made prior estimation are the following.

1. We divided our data set into eight industries, investigated in the previous section of the paper.

2. From each industry, we excluded all observations that contained implausible information: non-positive net sales revenues, value added, intangible assets, depreciation , wage costs or number of employees.

3. We also excluded those observations that changed industries during the seven year observation period, and this way our industry classification of the firm changed. (For example, textile industry in our sample contains industries from 17 to 19. If a firm was initially in industry 17, then changed to industry 18, then this firm was not excluded, as it operated in our classification of textile industry during the entire period. But, if a firm changed its classification from 17 to say, 29, then those observations with classification 29 were excluded from the textile industry, while observations with classification 17 could remain there.)

4. We also deflated the variables when it was appropriate.

Table 4 represents the remaining size of our data set after the exclusions.

Table 4

The effect of initial exclusions of the implausible observations

Industries	Initial number of observations	Initial number of firms	Number of observation after exclusions	Number of firms after exclusions
Food	1 547	221	1 463	221
Textile	2 429	347	2 300	346
Paper	1 505	215	1 405	214
Chemical	1 652	236	1 589	235
Metal	1 694	242	1 581	242
Machinery	3 101	443	2 885	441
Furniture	679	97	617	95
Electric	266	38	255	38
Total	*12 873*	*1 839*	*12 095*	*1 832*

Summary of the results

The Appendix contains all estimated parameters for the 64 models (8 possible models for 8 industries). We also included the Wald test-statistics considering the hypothesis that the production frontier of the industry is of constant returns to scale (i.e., the sum of the two reported estimated parameters is 1), and to the significance level of this test-statistics. Our main findings are as follows.

1. The estimated parameters are highly dependent of the variables chosen to measure output, labour input and capital input. Sometimes there is a conflict among the alternative models even in their returns to scale predictions (there are instances when some of the models indicate increasing, some other models decreasing returns to scale for the same industry). This is clearly a discrepancy that not only our parameter estimates are not robust to the choice of the model, but our return to scale estimates are either.

2. However, there is a systematic difference among the parameter estimates and return to scale predictions of different models. The most obvious difference is that replacing the wage cost variable to the number of employees variable, the sum of the estimated parameters systematically reduces. Sometimes this causes that predictions about an increasing/constant returns to scale with the wage cost variable (models 1, 2, 5, 6) change to predictions about constant/decreasing returns to scale with the number of employees variable (models 3, 4, 7, 8). The same occurs when replacing the value added variable (in models 5, 6, 7, 8) with revenue (models 1, 2, 3, 4). Finally, the incorporation of capital instead of depreciation tends to reduce the share of capital relative to the labour (i.e., smaller estimated parameters are obtained for the capital variable), while the sum of the two estimated parameters remains constant.

3. Let us summarize the results for the models containing our preferred dependent variable, value added (models 5-8).

– For the textile industry, all models predict increasing returns to scale.

– For industries of food, furniture and electricity, there is a consensus about the predictions of constant returns to scale.

– For paper and machinery, the prediction of all the models is decreasing returns to scale.

– For the chemical models with wage cost (5, 6) predict increasing, models with number of employees (7, 8) predict constant returns to scale.

– Finally, for the metal industry, models with wage cost (5, 6) predict constant, models with the number of employees (7, 8) predict decreasing returns to scale.

4. Finally, the relative labour intensiveness of the different industries matches our intuition. In our most preferred models, in model 5 and 7, the two industries with the highest labour shares are textile and furniture, which are clearly the most labour intensive industries. The most capital intensive industry is paper industry, with machinery also being relatively capital intensive in both cases.

Inefficiencies in different branches of the industry

From our production function estimates, for each industries we have calculated the average firm efficiencies, i.e. the average across firms inefficiency estimates. Different models lead to very similar results, the efficiencies in our two preferred models (5 and 7) are highly correlated (r=0.752). However, there is a systematic difference between the two measures: the average inefficiency terms estimated by model 5 (ineff5) are in each cases less than the model 7 estimations (ineff7); the reason for this was explained earlier. But luckily this does not change relative inefficiency measures, i.e. the order of industries with regard to inefficiencies. So both measures lead to the same results. The most efficiently operating branches (with the smallest inefficiency terms) are electricity, textile and paper industry; furniture, chemistry and food are around the average; while there are great inefficiencies in metal and machinery industries.

The main aim of the following section is to find some explanations for these differences both among and within different branches. Two possible sources of the between-industry differences are the extent of concentration of the industry and the share of foreign enterprises.

In the second part we will examine relative efficiencies within the industries: the effects of ownership structure, firm-size, the market share of the enterprises and the region of operation.

Concentration and inefficiencies

For each industries we calculated an index of the concentration, by calculating the share of the first 10 percent of the companies in the total value added and revenues (averages over the period).

Table 5

Concentration indices and average inefficiencies in different industries

Industries	Concentration		Ineff7	Ineff5
	value added	revenues		
	percent			
Food	57.77	57.71	0.5623	0.4377
Textile	54.18	60.83	0.4800	0.2794
Paper	60.59	63.26	0.6222	0.3539
Chemical	82.07	83.59	0.6711	0.4378
Metal	68.88	81.31	0.6524	0.5319
Machinery	73.51	77.26	0.6798	0.4907
Furniture	49.09	50.57	0.5178	0.3557
Electric	46.04	64.37	0.3788	0.2177

Note: Ineff7 and ineff5 stand for the estimated inefficiency measures in model 7 and model 5, respectively.

In Table 5 we can see the concentration indices and the average inefficiencies for the industries under investigation. It is apparent that there is a strong correlation between the two types of variables, and this is why we suppose that the higher the concentration is, i.e. the higher the monopolization in a specific industry is, the higher inefficiencies we expect to occur. In the case of the two variables in the figure, the correlation coefficient between them is 0.8905.

The share of foreign enterprises in the sector

The measure of the share of foreign enterprises in the sector can have opposite effect of what we have explained in the previous part; a higher foreign enterprise share in the sector probably refers to higher (international) market competition in the branch. To measure this effect we calculated two foreign enterprise share indices for each industry, i.e. the proportion of value added and the proportion of net sales revenues of foreign enterprises relative to all enterprises. We defined foreign owned companies as firms with more than 25 percent of foreign ownership on average over the period.

Table 6

Foreign share indices and average inefficiencies in different industries

Industries	Foreign share			Ineff7	Ineff5
	value added	revenues	number of firms		
	percent				
Food	76.40	73.74	33.80	0.5623	0.4377
Textile	47.78	48.58	30.98	0.4800	0.2794
Paper	68.15	72.76	31.73	0.6222	0.3539
Chemical	49.61	39.29	50.43	0.6711	0.4378
Metal	47.87	48.98	29.24	0.6524	0.5319
Machinery	67.26	72.56	32.11	0.6798	0.4907
Furniture	39.92	41.47	21.74	0.5178	0.3557
Electric	69.21	54.57	28.95	0.3788	0.2177
Total	60.26	56.71	33.86	0.4144	0.6018

The result is ambiguous. When measured with value added, foreign share shows a slight negative correlation with inefficiency terms, just as we would expect, but when measured with revenue the sign of the correlation coefficient turns into positive, though the coefficient is not significant (in neither cases). We can find the explanation for this phenomenon in Table 6. In the third column we can see the share of foreign enterprises in the different sectors when this share is measured simply by the number of firms. We can easily observe that the proportion declines to about the half compared to the previous ones, which means that foreign enterprises are usually the ones with higher than the average market share. This is reasonable as we think of the great number of multinational firms entering the Hungarian markets. So it seems that foreign enterprise presence not only means higher international competition but it is also connected with higher concentration in the branch,[14] which has just the opposite effect on efficiency. The outcome is somehow ambiguous.

The correlation coefficients between the inefficiency terms (ineff7 and ineff5) and the foreign share are –0.06 if it is measured with the value added, 0.18 and 0.16 respectively if the share is measured by the revenues.

The effect of ownership structure

In this section we transformed the standardized inefficiency terms into an interval between 0 and 100, therefore zero inefficiency term refers to a firm which is the most efficient, while a hundred indicates the less efficient company.

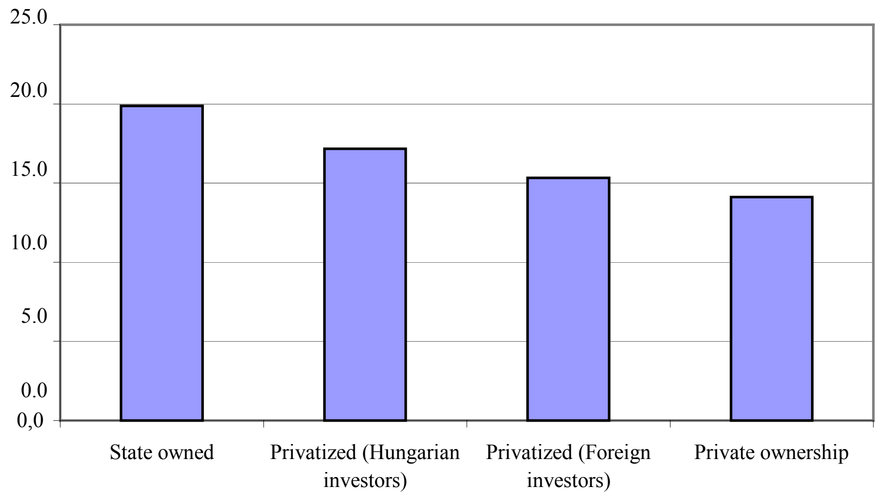
[14] This is justified if we examine the correlation coefficients between the proportion of the foreign firms and the concentration indices (as defined in Table 5). These are 0.75 and 0.64 (the former refers to the value added based concentration index, while the latter is calculated with the revenue based index).

a) *State and local government ownership*. To examine the effect of state ownership on productivity we have divided the firms in the sample into four main subgroups:

1. state owned during the whole period (1.1%),
2. privatized (state owned in 1992 but mainly private owned in 1998) to Hungarian investors (10.86%),
3. privatized to foreign investors (7.47%),
4. private (Hungarian and foreign) owned companies (average private ownership exceeds 30 percent). This means 74.24 percent of firms in the sample.

Figure 3 shows the average inefficiency terms in the defined subgroups.[15] We can see that private owned firms do outperform state owned ones. We can also conclude that privatization was successful when evaluating efficiencies: privatized firms perform better than state owned ones, especially when they are purchased by foreign investors.

Figure 3. Average inefficiencies in state and private owned firms
(model7)



Increasing inefficiencies in the state owned firms can be observed in nearly each industries (see Table 7). There are two interesting exceptions: the food and the metal industry. In both cases state owned firms operate nearly as efficiently as private owned, while privatized ones seem to be less efficient. This probably refers to the fact that in most cases the state sells its firms when they operate less efficiently, but especially in the food industry there are some huge companies that are world wide famous and operate so successfully (even if state owned) that the state do not want to sell them. An alternative explanation addresses the problems that firms just under privatization have to overcome: the costs of reorganization can be quite large, and normal operation is reached only after a certain period.

[15] Ineffiencies are measured by method 5 (explained in the previous sections).

Another interesting feature is that in electric industry there is a huge difference according to the effect of the direction of the privatization. Those firms that are sold to Hungarian investors are nearly as inefficient as state owned ones, while those that were purchased by foreign investors have significantly improved their efficiency.

Table 7

Average inefficiencies in different industries and different ownership
(method 5)

Industries	State owned	Privatized to Hungarian investors	Privatized to foreign investors	Private owned
Food	14.2	17.0	15.0	13.9
Textile	27.4	18.6	18.6	14.2
Paper	16.4	16.4	13.7	14.8
Chemical	25.2	17.2	15.2	14.1
Metal	14.8	17.9	16.8	13.7
Machinery	20.8	17.1	15.1	14.1
Furniture	–	10.8	23.1	14.3
Electric	21.9	21.5	9.9	11.3
Total	19.9	17.2	15.3	14.1

b) *Foreign investors*. Because of the huge changes in the ownership structure during the given period it seemed reasonable to examine the performance of the following subgroups of companies:[16]

1. foreign owned (during the whole period) (18.4%),
2. privatized to foreign owners (3.5%),
3. sold from Hungarian private owners to foreign investors (1.7%),
4. private owned (during the whole period) (57.7%),
5. state owned (during the whole period) (1.3%).

Figure 4 shows the average inefficiency terms in these subgroups (calculated with model 7). We can observe that foreign firms in Hungarian markets overperform even the domestic private ones, the effect is probably caused by the great inflow of multinational companies into the country.

Although privatization has a negative effect on efficiency among the firms that are purchased by foreign investors too, probably because of the reorganization costs, we would expect they will probably catch up after a short transitional period. But again we would like to note that privatization was successful in terms of improving the efficiency of their operation relative to state owned ones.

When examining these effects in different branches we can observe some interesting features of the Hungarian industry[17] (see Table 8). Parallel to the results of the previous

[16] In this case for simplicity ownership was defined according to the 'dominant' owner; for example we say an enterprise is state owned if the share of state among the owners is larger than 50 percent. This way of course some firms will be missing from the sample; the valid number of observations is 1062.

[17] In this case we could not evaluate state owned firms and those which have been sold from Hungarian to foreign private owners because of the small number of valid cases.

section we can see again the special case of the food sector, where both private and privatized firms perform worse than the overall average, while state owned ones show great advantages.

Figure 4. Average inefficiencies in foreign and Hungarian owned firms

Table 8

Average inefficiencies in different industries and different ownership

Industries	Foreign owned (the whole period)	Privatized to foreign owners	Private owned (the whole period)
Food	19.0	24.7	22.3
Textile	17.8	15.9	22.5
Paper	14.8	17.9	24.2
Chemical	15.6	19.4	23.6
Metal	19.1	17.9	20.7
Machinery	18.1	17.6	20.0
Furniture	13.1	29.6	19.6
Electric	8.3	15.6	8.5
Total	17.2	19.4	21.7

In textile industry we see right the opposite features. Those firms that were privatized to foreign investors are the most efficient ones, while the rest is less efficient. In chemical and furniture industry foreign firms are especially efficient relative to Hungarian ones, and also in metal and machinery branches, but with smaller differences among the two groups of firms. In electric industry we also see some very efficiently operating companies, owned by the private sector (either Hungarian or foreign), but we must note that in these categories there are only few firms in the sample, so the reliability of this result is quite low.

The effect of the size of the enterprise

It is also interesting to examine whether the size of the company is a good predictor of efficiency differences or not: can small companies catch up with big multinational ones? To measure this hypothesis we created three categories of enterprises in the sample:

– small enterprises (the average number of employees is smaller than 100 persons, 61.5 percent),
– medium size enterprises (the average number of employees is between 100 and 500 persons, 24.7 percent),
– large enterprises (the average number of employees exceeds 500 persons, 8.6 percent).

As Table 9 shows, larger enterprises are more efficient (have smaller average inefficiency terms) than smaller and medium ones. Indeed, we found significant negative correlation between size and inefficiency.[18] It seems that small enterprises cannot be as efficient as large multinational firms. The result is quite robust: according to Table 9, we reach the same conclusion in each of the industries. This can have strong implications for policy makers.

Table 9

Average inefficiency terms in small, medium and large enterprises

Industries	Small	Medium size	Large
	enterprises		
Food	22.3	18.1	18.9
Textile	21.3	20.4	17.7
Paper	21.7	18.6	10.8
Chemical	22.5	17.4	19.6
Metal	21.2	19.3	21.6
Machinery	21.1	21.8	16.8
Furniture	23.1	17.3	13.5
Electric	24.6	23.9	17.0
Average	21.7	19.6	18.0

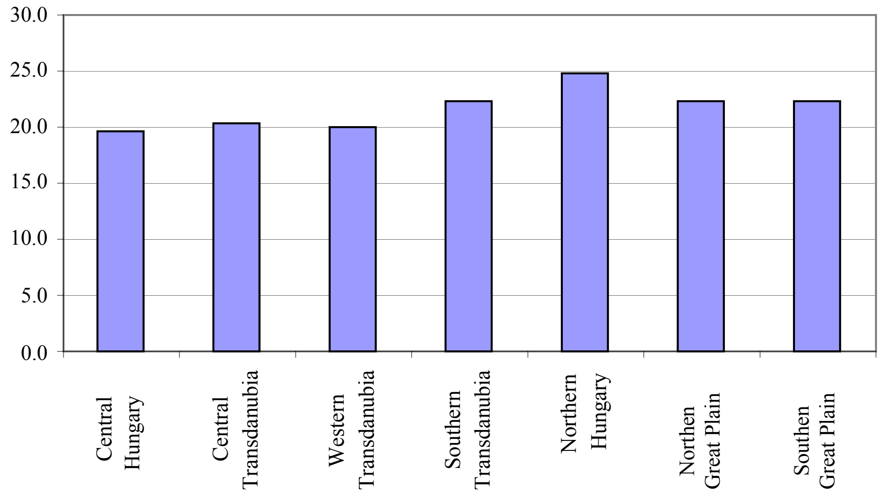
Region

It is well known that there are huge regional differences in the Hungarian industry. To explore regional differences in the performance of the enterprises we divided the country into seven regions: Central Hungary, Central Transdanubia, Western Transdanubia, Southern Transdanubia, Northern Hungary, Northern Great Plain, Southern Great Plain.

Efficiency terms on Figure 5. show that the centralized feature of the country leads to the relative advantages of the central part compared to some other regions. Transdanubia, especially Central and Western Transdanubia are also nearly as efficient as the central region of the country. Nevertheless there are huge inefficiencies in the operation of the firms in Southern Hungary and the Great Plain.

[18] The correlation coefficient is –0.67 in case of inefficiency measured by model 7.

Figure 5. Average inefficiencies in different regions



An alternative method of measuring determinants of inefficiency

To test for the significance of the previously analyzed relations we estimated efficiency equations. We regressed firm level efficiency terms against export share, proportion of state, foreign and private ownership and regions. Due to size considerations, we can present only a summary of our main findings.

The first observation is that the choice of the capital variable (depreciation against tangible assets) does not have much influence on the final results. On the other hand, replacing the labour input variable of the number of employees with wage costs has dramatic effects for the final results. Therefore we decided to split our results into two subgroups: to demonstrate them when the labour input variable is the number of employees, and when it is the wage costs.

To see all the significance relationship at the same time, we constructed 'significance tables', where we can see each significant variables for each industries. Table 10 contains the results when the labour input variable is the number of employees, while Table 11 has the same structure, but the labour input variable is the wage costs. In both tables, cells with dark backgrounds represent highly significant variables, while those with light background refer to weaker relationships (significant at 10 percent, but not significant at 5 percent).

The following conclusions can be drawn from the Tables 10 and 11.

1. The role of exports. The exporting companies do not seem to be more efficient than their non-exporting counterparts. The important exception can be found in the case of food industry, where there is a very small number of exporters (20 percent of the firms). These rare companies tend to be more efficient. In other industries, however, it is more common for a company to sell its products to foreign markets (in a typical industry the proportion of exporters is approximately 40 percent), then the competition at the domes tic markets among these exporting firms forces their non-exporting competitors to be more efficient, so that exporting alone is not an efficiency-improving activity. There is an interesting exception as well: in paper industry, exporting firms tend to be significantly less efficient. We explained this by industry-specific features: exporting firms are raw-material (like wood, etc.) exporters, while the non-exporter efficient firms (publishing and printing firms) operate mainly on domestic markets.

Table 10

Significance table of the explanatory variables when the labour input variable is the number of employees

Denomination	Food	Textile	Paper	Chemical	Metal	Machinery	Furniture	Electricity
Export (-)								
Export 2 (-)								
Export (+)								
Export 2 (+)								
State share (-)								
State share 2 (-)								
Privatized								
Foreign (-)								
Partly foreign (-)								
Partly foreign (+)								
Hungarian private owner (-)								
Central Transdanubia (+)								
Western Transdanubia (+)								
Southern Transdanubia (+)								
Northern Hungary (+)								
Northern Great Plain (+)								
Southhern Great Plain (+)								

Table 11

Significance table of the explanatory variables when the labour input variable is the wage cost

Denomination	Food	Textile	Paper	Chemical	Metal	Machinery	Furniture	Electricity
Export (-)								
Export 2 (-)								
Export (+)								
Export 2 (+)								
State share (+)								
State share 2 (+)								
Privatized								
Foreign (-)								
Partly foreign (-)								
Partly foreign (+)								
Hungarian private owner (-)								
Central Transdanubia (+)								
Western Transdanubia (+)								
Southern Transdanubia (+)								
Northern Hungary (+)								
Northern Great Plain (+)								
Southern Great Plain (+)								

Note: In Table 10 and 11 the directions of impact on inefficiency are in parenthesis.

2. The role of state ownership. We would expect that firms under public ownership operate less efficiently, but this is not justified in our data set. In some cases we saw exactly the opposite: state owned companies were found to be more efficient. We explained this phenomenon by the fact that the number of state-owned companies is recently very small, in a typical industry, it is around 10 percent; among these companies there are several strategically important, relatively well-performing companies. (This is especially true for the electricity sector, where the state was reluctant to sell the big national suppliers.) Though, it is still interesting that we have found inefficiency corresponding to state in only one instance (at the chemical industry, when the labour input variable is wage costs). Another significant issue is privatization: we expected that inefficiencies can be explained (at least to some extent) by the dramatic changes in the ownership structure. But we could not detect any evidence that newly privatized companies were more efficient. This may be explained by the fact that: first, the observation period is too short to detect any significant change in efficiency for a specific company; second, the majority of private firms gave the controlling rights for the former management and workers, who had limited financial backgrounds for the necessary investments. (This is especially true for the smaller firms.)

3. The role of foreign ownership. This is the variable that seems to explain the most successfully the differences in inefficiencies. According to almost all models in all industries under investigation, dominant (above 50 percent) foreign control increases efficiency. However, the role of partial foreign ownership is not so obvious. We have found evidence that it may even reduce efficiency (in metal and machinery).

4. The role of domestic private ownership. Here we observed a very interesting pattern of significance: when our labour input variable is the number of employees, Hungarian private ownership tends to have not a significant effect on efficiency. However, when labour input is measured in wage costs, Hungarian private firms are found to be much more efficient. This may be explained by the differences in wage levels among multinational and other companies: when we measure efficiency per unit wage costs, those Hungarian firms that pay lower salaries outperform the other ones. This is not true, however, if we consider ‘raw labour’, i.e. efficiency per worker.

5. The role of regional dummies. There is a sharp difference between the two types of models. When we consider the number of employees, Budapest and the Central region are the most efficient on average. (The estimated regional dummies are almost always positive, relative to East Hungary, though sometimes insignificant.) Though changing to wage costs as labour input variable, Budapest and the Central region (which is characterized by much higher wage levels) looses its efficiency advantage, and several times it becomes the least efficient region. (In this case the estimated parameters for the regional dummies tend to turn into negative, though remaining mainly insignificant.)

CONCLUSION

In this paper we estimated industry-specific production function frontiers and found that our estimates are highly dependent on the choice of input and output variables. Based on simple statistical methods, and on theoretical arguments, our preferred output variable is value added, and our preferred capital input variable is depreciation. We cannot choose between wage costs and number of employees as a labour input measure, as it influences significantly our final results.

The results show that average efficiency is highest in textile, electric and paper industries, while machinery and metal industries are the least efficient on average. We explained the differences by several factors. When examining all industries together, we found that the highest the concentration is, the highest is the average inefficiency; private and foreign owned firms generally outperform the rest of the companies. Large companies tend to be more efficient as well and regional differences do not play an important role in explaining inefficiency, the western and central region being only slightly more efficient than eastern firms.

We also tried to explain firm-specific inefficiencies in all industries separately. Our main results were that the only variable that could robustly (i.e., independently from the model setting and the industry under investigation) explain higher efficiency is foreign ownership. State owned companies tend to be as efficient as privatized ones. Export-orientation is also a weak indicator of higher efficiency, examined at industry level. Hungarian private ownership also tends to increase efficiency in those models when the labour input is measured as wage costs. Regional dummies gain significance only when the labour input variable is the number of employees.

APPENDIX

Estimated parameters for different models

LHS variable	RHS variables: labour	RHS variables: capital	Variable coefficient for labour	Variable coefficient for capital	Wald test statistics	Significance level
			Food			
Revenue	Wage cost	Depreciation	0.83	0.16	0.64	0.43
Revenue	Wage cost	Capital	0.92	0.06	2.34	0.13
Revenue	Number of employees	Depreciation	0.66	0.31	2.64	0.10
Revenue	Number of employees	Capital	0.81	0.12	9.03	0.00
Value added	Wage cost	Depreciation	0.88	0.13	0.36	0.55
Value added	Wage cost	Capital	0.93	0.08	0.42	0.52
Value added	Number of employees	Depreciation	0.70	0.33	1.60	0.21
Value added	Number of employees	Capital	0.82	0.20	0.70	0.40
			Textile			
Revenue	Wage cost	Depreciation	0.87	0.16	3.39	0.07
Revenue	Wage cost	Capital	0.93	0.08	1.85	0.17
Revenue	Number of employees	Depreciation	0.68	0.29	3.99	0.05
Revenue	Number of employees	Capital	0.76	0.19	8.87	0.00
Value added	Wage cost	Depreciation	0.99	0.07	46.36	0.00
Value added	Wage cost	Capital	1.04	0.03	41.50	0.00
Value added	Number of employees	Depreciation	0.84	0.24	25.24	0.00
Value added	Number of employees	Capital	0.91	0.15	14.74	0.00
			Paper			
Revenue	Wage cost	Depreciation	0.59	0.29	54.44	0.00
Revenue	Wage cost	Capital	0.71	0.12	80.05	0.00
Revenue	Number of employees	Depreciation	0.43	0.39	80.67	0.00
Revenue	Number of employees	Capital	0.55	0.15	179.49	0.00
Value added	Wage cost	Depreciation	0.73	0.22	10.93	0.00
Value added	Wage cost	Capital	0.85	0.09	11.32	0.00
Value added	Number of employees	Depreciation	0.49	0.40	25.91	0.00
Value added	Number of employees	Capital	0.62	0.15	80.98	0.00
			Chemistry			
Revenue	Wage cost	Depreciation	0.77	0.19	8.44	0.00
Revenue	Wage cost	Capital	0.85	0.11	6.07	0.01
Revenue	Number of employees	Depreciation	0.60	0.33	11.53	0.00
Revenue	Number of employees	Capital	0.74	0.18	16.83	0.00
Value added	Wage cost	Depreciation	0.87	0.16	6.60	0.01
Value added	Wage cost	Capital	0.97	0.07	7.59	0.01
Value added	Number of employees	Depreciation	0.62	0.37	0.14	0.71
Value added	Number of employees	Capital	0.80	0.18	1.46	0.23

(Continued on the next page.)

(Continuation.)

LHS variable	RHS variables: labour	RHS variables: capital	Variable coefficient for labour	Variable coefficient for capital	Wald test statistics	Significance level
		Metal				
Revenue	Wage cost	Depreciation	0.74	0.24	1.79	0.18
Revenue	Wage cost	Capital	0.85	0.11	4.10	0.04
Revenue	Number of employees	Depreciation	0.50	0.39	40.39	0.00
Revenue	Number of employees	Capital	0.60	0.20	91.17	0.00
Value added	Wage cost	Depreciation	0.89	0.13	0.97	0.33
Value added	Wage cost	Capital	0.97	0.04	0.54	0.46
Value added	Number of employees	Depreciation	0.56	0.34	22.38	0.00
Value added	Number of employees	Capital	0.68	0.17	44.40	0.00
		Machinery				
Revenue	Wage cost	Depreciation	0.71	0.25	14.33	0.00
Revenue	Wage cost	Capital	0.82	0.13	14.41	0.00
Revenue	Number of employees	Depreciation	0.51	0.37	56.84	0.00
Revenue	Number of employees	Capital	0.67	0.19	80.60	0.00
Value added	Wage cost	Depreciation	0.83	0.15	3.99	0.05
Value added	Wage cost	Capital	0.91	0.07	3.97	0.05
Value added	Number of employees	Depreciation	0.59	0.31	39.14	0.00
Value added	Number of employees	Capital	0.74	0.14	54.08	0.00
		Furniture				
Revenue	Wage cost	Depreciation	0.77	0.10	29.93	0.00
Revenue	Wage cost	Capital	0.82	0.04	30.54	0.00
Revenue	Number of employees	Depreciation	0.60	0.23	28.16	0.00
Revenue	Number of employees	Capital	0.68	0.13	31.28	0.00
Value added	Wage cost	Depreciation	0.91	0.09	0.04	0.85
Value added	Wage cost	Capital	0.94	0.05	0.01	0.93
Value added	Number of employees	Depreciation	0.68	0.27	2.35	0.13
Value added	Number of employees	Capital	0.76	0.18	3.11	0.08
		Eletricity				
Revenue	Wage cost	Depreciation	0.39	0.29	101.18	0.00
Revenue	Wage cost	Capital	0.54	0.17	72.39	0.00
Revenue	Number of employees	Depreciation	0.22	0.37	128.61	0.00
Revenue	Number of employees	Capital	0.38	0.19	115.08	0.00
Value added	Wage cost	Depreciation	0.82	0.20	0.92	0.34
Value added	Wage cost	Capital	0.94	0.10	4.22	0.04
Value added	Number of employees	Depreciation	0.63	0.36	0.24	0.63
Value added	Number of employees	Capital	0.85	0.17	0.56	0.46

REFERENCES

AIGNER, D. – CHU, S. (1968): On estimating the industry production function. *American Economic Review*, No. 58. p. 826–839.

AIGNER, D. – LOVELL, K. – SCHMIDT, P. (1977): Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics,* Vol. 6. No. 1. p. 21–37.

ALCHIAN, A. A. (1965): Some economics of property rights. *Il Politico,* Vol. 30. No. 4. p. 816–829.

ALCHIAN, A. A. – KESSEL, R. A. (1962): Competition, monopoly, and the pursuit of money. In: *Aspects of Labour Economics*. Princeton University Press for The National Bureau of Economic Research, Princeton. p.157-175.

AVERCH, H. – JOHNSON, L. L. (1962): The behaviour of the firm under regulatory constraint. *American Economic Review*, Vol. 52. No. 5. p.1052–1069.

BATTESE, G. – COELLI, T. (1988): Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data. *Journal of Econometrics,* Vol.38. No. 3. p. 387–399.

BECKERS, D. – HAMMOND, C. (1987): A tractable likelihood function for the normal-gamma stochastic frontier model. *Economics Letters,* No. 24. p. 33–38.

BERNSTEIN, M. A. – FELDMAN, S. L. – SCHINNAR, A. P. (1990): Impact of pollution controls on the productivity of coal-fired power plants. *Energy Economics,* Vol. 12. No. 1. p. 11–17.

DEBREU, G. (1951): The coefficient of resource utilization. *Econometrica,* Vol. 19. No. 3. p. 273–292.

GABRIELSEN, A. (1975): *On estimating efficient production functions*. Working Paper, No. A-85, Chr. Michelsen Institute, Bergen, Norway.

GREENE, W. (1980): Maximum likelihood estimation of econometric frontier functions. *Journal of Econometrics,* Vol. 13. No. 1. p. 27–56.

GREENE, W. (1990): A gamma-distributed stochastic frontier model. *Journal of Econometrics,* Vol.46. No. 1–2. p. 141–163.

GREENE, W. (1993): The econometric approach to efficiency analysis. In: *The measurement of productive efficiency, techniques and applications. Fried, H. O. – Lovell, C. A. K. – Schmidt, S. S.* (ed.) Oxford University Press.

GREENE, W. (1997): *Econometric Analysis*. Prentice-Hall Inc. New Jersey.

HICKS, J. R. (1935): The theory of monopoly: A survey. *Econometrica*, Vol. 3. No. 1. p. 1–20.

JONDROW, J. ET AL. (1982): On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics,* Vol. 19. No. 2–3. p. 233–238.

KOOPMANS, T. C. (1951): An analysis of production as an efficient combination of activities. In: *Koopmans, T. C.* (ed.) *Activity analysis of production and allocation*. Cowles Commission for Research in Economics, John Wiley and Sons, Inc. New York.

MEEUSEN, W. – VAN DEN BROECK, J. (1977): Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review,* Vol. 18. No. 2. p. 435–444.

SHEPHARD, R.W. (1970): *Theory of cost and production functions*. Princeton University Press, Princeton.