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Production Functions and Efficiency Analysis of the Siberian Forest Industry: An Enterprise Survey 1989 and 1992

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Foreword

The technological state and upgrading are the most important determinants of competitiveness for the Siberian forest sector. The technological properties and the geography of output and efficiency are investigated in this paper. This is a first attempt to quantify and explain the differences in productive efficiency on an enterprise level. From numerous personal visits to enterprises in the region, we know that the financial balance sheet data prior to and after the collapse of the Former Soviet Union are, in general, not reflecting the true state of an enterprise. Instead, it was decided to use physical output data from 1989 and 1992 to quantify the technological state of the enterprises. These two years were selected for two reasons: (1) enterprises were still tightly monitored by the statistical organs which is reflected in the high reliability of the data; and (2) enterprises were producing close to their production capacity which allows us to measure technical inefficiency. The data was collected by a large network of regional experts in the field and were appraised for consistency at IIASA.

Our findings indicate that on the micro-level economies of scale in production are even more important than on the regional level. Efficiency differences are small within Siberia compared to the large productivity gap of current western technologies. Labor productivity could rise by a factor of 6 to 40 if the latest western technology were introduced. This will, of course, have dramatic effects on the employment situation in the forest sector, which has its operations primarily in rural mono-enterprise towns. As soon as forest enterprises adopt a high productive and more economical (even under Russian conditions) technology, it can be predicted that a large number of workers will be omitted from the payroll of forest industrial enterprises. Currently, the Russian Federation lacks policy measures and effective programs to deal with large scale unemployment in rural areas, and there are no programs to facilitate labor mobility of rural workers. This lack of support has already created severe social hardship and will, according to our predictions, pejorate in the near future when enterprises start to restructure and radically increase productivity in a post-barter economy. There is also no sign that the government will be able to do something about poverty in the rural areas of Russia.

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1 Introduction

It is well known that in the Former Soviet Union large economic inefficiencies were present in the system of a planned economy. These inefficiencies were not only related to the use of raw materials, but also to labor and energy use. An elaborate pricing system could mask most of these inefficiencies for a long time but the extent and distribution of these inefficiencies became apparent during the transition to a market economy. The entire manufacturing sector requires restructuring and technological upgrading. In this respect, it is important to target specific inefficiencies. A first step is to characterize and quantify inefficiencies and understand the properties of current and future production technology.

From a methodological point of view the analysis of single enterprise performance is difficult with Russian data for the following reasons:

- The assumptions of profit maximization and cost minimization can not be applied;
- Inputs are not reported separately for different outputs; and
- Large uncertainties about data quality exist.

However, these reasons also apply to the analysis of more aggregate data. At best, the problems concerning data quality are equally large. The advantage of working with individual company data is that, in the course of time through extensive study tours, one understands the real workings of the enterprises. In addition, we were able to acquire technical descriptions of the technology used, which certainly helped to validate our results.

Data Envelopment Analysis (DEA), as discussed below, has proved to be valuable for many empirical applications. The absence of *a priori* assumptions have resulted in an efficient frontier estimation in the non-profit sector, the regulated sector, and the private sector of western economies.

The efficiency of a production unit can be described by comparing observed and optimal values of outputs and inputs. This comparison can take the form of the ratio of observed to maximum potential output obtainable from a given input, or the ratio of minimum potential to observed input required to produce a given output, or a combination of both. In these comparisons, the optimum is defined in terms of production possibilities, and efficiency is technical. It is also possible to define the optimum in terms of the behavioral goal of the production unit. In this event, efficiency is economic, and measured by observed and optimum costs, revenue, profit, or whatever the production unit is assumed to pursue subject, of course, to the appropriate constraints on quantities and prices.

In this paper, I will give a short description of the method applied to measure inefficiencies using a mathematical programming approach (Ali and Seiford, 1994),[1] and present some basic statistical analysis of the efficiency scores of individual enterprises of the Siberian forest industry. The differences and analogies to the standard econometric approach will be presented and production functions will be estimated using simple econometric models including calculated efficiency scores.

2 Mathematical Programming Approach to Efficiency Measurement Data Envelopment Analysis (DEA)

In their original study, Coopers *et al.*, (1978), described the DEA methodology as a "mathematical programming model applied to observed data that provides a new way of obtaining empirical estimates of extremal relationships such as the production functions and/or efficient production possibility surfaces that are the cornerstones of modern economics".

In standard microeconomic theory, the production function can be interpreted as forming the basis for a description of input–output relationships of a firm, groups of firms, or even of an entire sector. Alternatively, the production function constitutes a frontier for the production possibility set. Efficiency computations can be made relative to this frontier if it is known. However, in practice, one has only data — a set of observations for each decision making unit (DMU) corresponding to the achieved output levels for given input levels. Thus, the initial task is to determine which of the set of $DMUs$, as represented by observed data, form the empirical production function or envelopment surface.

We assume that there are n $DMUs$ to be evaluated. Each DMU consumes varying amounts of m different inputs to produce s different outputs. Specifically, decision making units l, consume $x_{il} \leq 0$ amount of input i and produces $y_{rl} \leq 0$ amount of output r. X_l and Y_l will denote vectors of input and output values for DMU_l respectively. The models of DEA seek to determine which of the n decision making units determine an envelopment surface. This envelopment surface is referred to as the empirical production function or the efficient frontier. DEA provides a comprehensive analysis of relative efficiencies for multiple input and output situations by evaluating each DMU and measuring their performance relative to an envelopment surface composed of other $DMUs$. Units that lie on the surface are efficient in this terminology but units that do not lie on the surface are called inefficient and the analysis allows for measuring their relative inefficiency.

[1]The accuracy of the GAUSS program was checked with sample data as published in Ali and Seiford (1994).

There are two basic types of envelopment surfaces in data envelopment analysis, variable-returns-to-scale (VRS) and constant-returns-to-scale (CRS) surfaces.

2.1 Variable-returns-to-scale (VRS) model

The VRS envelopment surface consists of portions of supporting hyperplanes in R^{m+s} that form particular facets of the convex hull of the points (Y_j, X_j) of the $DMUs$, $j = 1 - \cdots - n$. The general equation of a hyperplane in R^{m+s} is given by:

$$\sum_{r=1}^{n} \mu_r y_r - \sum_{i=1}^{m} \nu_i x_i + \omega = 0 \tag{1}$$

This is a supporting hyperplane if all of the points (Y_j, X_j) lie on or beneath the hyperplane and, additionally, the hyperplane passes through at least one of the points. These conditions can now be written as a linear programming problem as follows:

$$VRS_P(Y_l, X_l):$$

$$\begin{array}{lrcll}
\overset{max}{\mu_r, \nu r, \omega} & \sum_{r=1}^{s} y_{rl}\mu_r - \sum_{i=1}^{m} x_{il}\nu i + \omega & & & \\
 & \sum_{r=1}^{s} y_{rl}\mu_r - \sum_{i=1}^{m} x_{il}\nu i + \omega & \leq & 0 & for\ j = 1 - \cdots - n \\
 & \mu_r & \geq & 1 & for\ r = 1 - \cdots - s \\
 & \nu_r & \geq & 1 & for\ i = 1 - \cdots - m
\end{array} \tag{2}$$

The set of constraints insures that all points lie on or below the supporting hyperplane. The objective function measures the distance from DMU_l to this hyperplane. Maximization of the objective function selects a hyperplane which minimizes this distance. The supporting hyperplane for efficient $DMUs$ serves as the closest supporting hyperplane for an inefficient DMU.

The representation of the problem, as stated above, makes it difficult to identify the underlying facet structure. An accessible representation of the facet structure is given by solving the linear programming dual. This makes a convex combination of the reference $DMUs$ possible. The dual problem can be stated as follows:

$$VRS_E(Y_l, X_l):$$

$$\begin{array}{lrcll}
\overset{min}{\lambda_r, s_r, e_i} & -(\sum_{r=1}^{s} s_r + \sum_{i=1}^{m} e_i) & & & \\
 & \sum_{j=1}^{n} y_{rj}\lambda_j - s_r & = & y_{rl} & r = 1 - \cdots - s
\end{array}$$

$$\begin{aligned}
-\sum_{j=1}^{n} x_{ij}\lambda_j - e_i &= -x_{il} \qquad i = 1 - \cdots - m \\
\sum_{j=1}^{n} \lambda_i &= 1 \\
\lambda_j &\geq 0, \qquad j = 1 - \cdots - n \\
s_r &\geq 0, \qquad r = 1 - \cdots - s \\
e_i &\geq 0, \qquad i = 1 - \cdots - m
\end{aligned} \tag{3}$$

The first s constraints correspond to the s outputs, the m constraints to the m inputs, and the last constraint, $\lambda_j \geq 0$, is associated with the variable ω. The variables of the dual problem are non-negative. The optimal solution to VRS_E and (Y_l, X_l) consists of the s-vector of output slacks, s_l, and m-vector of excess inputs, e_l, and the n-vector λ_l. If $\lambda_{ll} = 1$ then DMU_l lies on the envelopment surface and is efficient. For a DMU that does not lie on the envelopment surface, the point $(\hat{Y}_l, \hat{X}_l)$ is referred to as the projected point. The projected point can equivalently be expressed as:

$$(\hat{Y}_l, \hat{X}_l) = (\sum_{j=1}^{n} \lambda_i^l Y_j, \sum_{j=1}^{n} \lambda_i^l X_j) = (Y_l + s^l, X_l + e^l) \tag{4}$$

The vector s^l is, again, the vector of output slacks and the m-vector e^l is the vector of excess inputs.

2.2 Constant-returns-to-scale (CRS) model

A CRS envelopment surface consists of hyperplanes in R^{m+s} that form particular facets of the conical hull of the points (Y_j, X_j), where $j = 1 - \cdots - n$). In contrast to the previous surface, all supporting hyperplanes for a CRS envelopment pass through the origin. Thus, $\omega = 0$, and the equation for a hyperplane reduces to:

$$\sum_{r=1}^{n} \mu_r y_r - \sum_{i=1}^{m} \nu_i x_i = 0 \tag{5}$$

Computationally, the CRS multiplier and dual programs are very similar to the VRS program. In the dual program the only difference is that the restriction $\sum_{j=1}^{n} \lambda_i = 1$ is missing in the CRS formulation. Since the constraint set for the dual CRS is less restrictive (the convexity constraint is absent), lower efficiency scores are possible and, consequently, also fewer $DMUs$ are declared efficient.

2.3 Measurement of efficiency and the output oriented model

The DEA analysis, as discussed above, requires the solution of n linear programming problems for each DMU. In the evaluation of unit l we solve the LP problem for the particular envelopment surface and obtain a facet-defining hyperplane of the envelopment surface and a projected point $(\hat{Y}_l, \hat{X}_l)$ that lies on the hyperplane. Measures of efficiency for DMU_l address the discrepancy between the point (Y_l, X_l) and the projected point $(\hat{Y}_l, \hat{X}_l)$ on the envelopment surface. The points $(\hat{Y}_l, \hat{X}_l)$ and (Y_l, X_l) lie on parallel planes that differ by the constant $\delta^l = -\mu^l \hat{Y}_l - Y_l - \nu^l X_l - \hat{X}_l = -\mu^l s^l - \nu^l e^l$. The discrepancy is calculated with respect to the optimum value of the objective function.

In an output oriented model, the output vector can be increased proportionally by the factor ρ in order to project the (Y_l, X_l) along the vector s^l. The amount of proportional increase of outputs ρ for the obtained projected points is given by:

$$\rho = \overset{min}{r} \frac{\hat{y_{rl}} - y_{rl}}{y_{rl}} \leq 0 \tag{6}$$

ρ determines the extent to which inefficiency can be reduced by proportional output augmentation. The output oriented models for CRS an VRS envelopment are stated as follows:[2]

CRS output orientation — first stage:

$$\begin{array}{rcl} \overset{max}{\phi, \lambda, s, e} \;\; \phi & & \\ -Y\lambda + \phi Y_l + s & = & 0 \\ X\lambda + e & = & X_l \\ \lambda \geq 0, e \geq 0, s & \geq & 0 \end{array} \tag{7}$$

CRS output orientation — second stage:

$$\begin{array}{rcl} \overset{min}{\lambda, s, e} \;\; -(1s + 1e) & & \\ Y\lambda - s & = & Y_l \\ -\phi^l X\lambda - e & = & -X_l \\ \lambda \geq 0, e \geq 0, s & \geq & 0 \end{array} \tag{8}$$

The computation of the first and second stage problem of the VRS output orientation are analogous to the CRS computation. The only difference is, again, that the VRS constraint set is extended by $1\lambda = 1$. The resulting efficiency scores of both models are unit invariant.

2.4 Calculation of scale inefficiencies

Efficiency can, in principal, be divided into two components: allocative and technical efficiency. The allocative efficiency component can be described as the ratio

[2]The second stage was programmed, however, for computational convenience not analyzed. With test runs, I confirmed that the differences between the first and second stages for the calculated ϕ were minimal for all $DMUs$.

between the distance of the enveloping VRS hull and the distance of the observed DMU from the input–output many-fold. The allocative efficiency can be associated with managerial (tactical) inefficiencies and are identical with the VRS-efficiency score. The technical efficiency component can be associated with the strategical imperfections of decisions of the overall input–output combination of a DMU. In the DEA terminology the technical inefficiency is called scale efficiency ς and is calculated by the formula:

$$\varsigma = \frac{\phi_{VRS}}{\phi_{CRS}}. \tag{9}$$

ς measures the distance between the VRS hull and the CRS hull for a projected DMU_l.

3 Data

The data was collected by a Russian team of collaborators and made available to the International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria. This data stems from individual enterprises of the forest industry of Siberia. Enterprises which were not randomly selected; only those enterprises, known by the team of data collectors, were sampled. The data set, as presented here, describes the situation of a typical "lespromhoz". These are enterprises producing roundwood and/or lumber. In some cases, the enterprise also produced other output, such as resins, tannin oils, and cedar nuts. This output was not included in the data set analyzed.

Several appraisals have been written on data quality. It was concluded that some of the data items are very doubtful or, at least, need further verification. Data was collected for 1989 and 1992. In 1989, there was still the planned economy, whereas in 1992, market reforms had already begun. In updating our database we learned that not only data quality rapidly declined, but also many indicators were simply not collected any more (e.g., energy use), or had completely lost their meaning and were subject to manipulation (e.g., capital). In light of the fact that GosKomStat lost virtually all of its institutional powers, there should be more discussion among empirical transition economists about which questions can be tackled with the uncertain database and which questions should and should not be tackled.

4 Results

4.1 Geographic distribution of efficiency

Data was analyzed separately for 1989 and 1992.[3] One-way analysis of variance revealed that efficiencies (VRS and CRS) were significantly different across regions. The analysis of variance for the variable $\phi_{92,CRS}$ is given in *Table 1.* A basic statistical

[3] One-way ANOVA of the efficiency scores with the factor time yielded significant results with unrestricted data only.

description of $\phi_{92,CRS}$ of lespromhozes distributed over various regions is given in *Table 2*.

Table 1: One-way ANOVA statistics of $\phi_{92,CRS}$

Source	D.F.	SSq	MSq	F-Ratio	F-Prob
Between Groups	4	0.2073	0.0518	4.2705	0.0029
Within Groups	114	1.3834	0.0121		
Total	118	1.5907			

Table 2: Basic statistical indicators of $\phi_{92,CRS}$

Region	Count	Mean	Deviation	Error
Krasnoyarsk	28	0.8552	0.1439	0.0272
Irkutsk	35	0.9450	0.0762	0.0129
Kemerovo	12	0.8502	0.1877	0.0542
Novosibirsk	15	0.9491	0.0469	0.0121
Tjumen	29	0.8777	0.0862	0.0160
Total	119	0.8984	0.1161	0.0106

The lespromhozes of the Irkutskii oblast were the most efficient. This observation from the data can also be verified by the fact that some of the latest development projects of the forest industry in Siberia were located in this oblast. Within the oblast, the most efficient lespromhozes are located around the large wood-processing plants, Ust-Illimsk and Bratsk. Interestingly, stock shares of these two enterprises, publicly traded at the Moscow stock market, were among the most profitable of all the industrial stocks in the Russian Federation at the time the Moscow Stock Exchange (MSE) saw its first hausse.

Although VRS and CRS efficiency scores showed significant differences across Siberian regions, scale efficiencies did not follow this pattern (*Table 3*).

Table 3: F-statistics of one-way ANOVA of efficiency scores with geographic region as a factor

Significance level of the F-test	
ϕ_{92VRS}	0.0317
ϕ_{89CRS}	0.0006
ϕ_{89VRS}	0.0171
ς_{92}	0.6274
ς_{92}	0.2446

4.2 Enterprises forming the efficient frontier

Efficient lespromhozes were, in all cases, part of some of the few enterprise associations (obedinenije). Enterprises of the following enterprise associations lie on the efficient frontier:

- HA Bratskles
- HA Illimskles
- TPO Ust–Illimskii
- TPO Tjumenlesprom
- Novosibirskii Koncern
- Novosibirskoe LTPO

4.3 Explaining efficiencies

An interesting question from a methodological point of view is: How Ordinary Least Squares (OLS) would explain efficiency scores with the variables by which they were generated? Equation 11 was used to analyze this relationship.

$$\begin{aligned}\phi_{t;CRS,VRS} &= \beta^{1}_{t;CRS,VRS} + \beta^{O}_{t;CRS,VRS} * Output_{i,t} \\ &\quad + \beta^{I}_{t;CRS,VRS} * Input_{j,t} + \epsilon \end{aligned} \tag{10}$$

The adjusted $R^2 - s$ of this multiple regression procedure never exceeded the level of 0,25. An increase in the R^2 was observed when restricting data by $\phi_{CRS} \geq 0,85$ and $\phi_{VRS} \geq 0,85$. This restriction eliminated outliers, which explains the increase in the R^2. There is also a high degree of multicollinearity in this model. Calculating the eigenvector of the explaining variable matrix revealed a high degree of multicollinearity. A strong near dependency between the produced lumber and the amount of roundwood used to produce lumber was detected. Erasing the roundwood input variable from the ill-specified data matrix results in considerable changes in the β-values, as one would expect in such a situation of high multicollinearity. I proceeded to remove the variables "residual value of productive assets" and "electricity" from the data matrix for the same reason. This produced results which did not improve the quality of the model. Additionally, it should be mentioned that when restricting again ϕ, some of the β-values even changed signs. This would mean that an input would influence the efficiency score as if it were an output and vice-versa. However, it should be emphasized that when estimating these equations, when the $\phi - s$ were restricted, the number of observations per explaining variable never exceeded 25. Estimating equation (10) in logarithmic form also did not improve the quality of the model. The *facit* of these results is that the functional form of the envelopment surface does not correspond to the fitted line of the OLS. Thus, log-linear regression models would fail to capture the production relations of the best practice technology.

It is in the nature of roundwood and lumber production that productivity and efficiency must change with the average log-volume and the average transportation distance from the logging site to the lower landing where logs are usually processed further. Furthermore, I had the variables coefficient-of-utilization-of-productive-machinery, amount-of-hardwoods-processed, average-stand-density, and geographic location at my disposal for analysis. There is no correlation between all these variables and the CRS or VRS efficiency score whatsoever. This is a rather sobering result and places a big question on the overall data quality, but could however, also be related to technical adjustment factors and the price structure under the planned economy system. More generally, one is inclined to put more trust in engineering than economic data. This is especially true for data from transition economies.

4.4 Explaining scale inefficiencies

By pooling data and analyzing production categories separately, scale inefficiencies could not be explained with the size of output in neither physical nor financial terms. Although $R^2 - s$ never exceeded the level of 0.4, the regression coefficients were always different from zero (significance level 10%) and the slopes were consistently positive. This is an indication for increasing returns to scale technologies. The estimation of a Cobb-Douglas production function also reveals increasing returns to scale technology. It can, thus, be concluded that on the enterprise level economies of scale were already present, but increased during transition.

4.5 Explaining efficiency decline

Linear multiple regression was used to explain efficiency decline. Relative and absolute decline of the explaining input and output variables were used. No linear model could be specified explaining a decline of $\phi_{CRS,VRS}$. Adjusting for multicollinearity and restriction of data never yielded significant F-values and $R^2 - s$ were also always below 0.4. Again the restricted equations were estimated with less than 25 observations per explaining variable.

4.6 Estimating Cobb-Douglas production functions

The efficiency score proved to be very useful to identify enterprises which were either very inefficient and should therefore not enter an overall production function of an entire sector, or which were in fact efficient, but some of the output was not recorded in the database at hand. For the econometric estimation of the production function of lespromhozes, data was restricted to efficiency scores $\phi \geq 0.7$. This range seems to be reasonable from glancing at the data and having some knowledge from visits to some of the enterprises listed in the analyzed data set.

A production function[4] was estimated in the Cobb-Douglas form according to equation 11:

[4] The following abbreviations were used: L for labor, E for electrical energy, F for fuel, R for roundwood used for lumber production, and K for the residual value of productive assets.

$$Y = e^{\beta_0} * L^{\beta_L} * E^{\beta_E} * F^{\beta_F} * R^{\beta_R} * K^{\beta_K} * e^u \quad (11)$$

The estimated elasticities of the inputs are listed in *Table 4*. The $R^2 - s$ of the OLS and the 2SLS were above 0.83 and all F-tests were significant for the estimated equations. In the unrestricted case the residuals of the OLS estimation were textbook-like normally distributed. The calculation of a 2SLS with the instruments L, E, F, R, K and the efficiency score did not virtually change the estimators on a two-digit precision level as can be seen in *Table 4*. But, using instrument variables, L, E, F, R, K, the average log-volume, the average transportation distance, and geographic location, the goodness of fit indicators did not improve. This might be due to a loss in the degrees of freedom and/or due to the data quality of the instruments. Enterprises were more capital and labor efficient in 1992, as can be seen from the capital and labor elasticities in the production functions.

Another possibility is to include the calculated efficiency scores directly in the Cobb-Douglas production function. The argument for a correction of the output is that we are more interested in the production function of efficient $DMUs$. By this we mean the technical potential, where managerial inefficiencies and inefficiencies due to demand shocks are excluded from the analysis. We are, in fact, interested in an hypothetical output $Y^{hy} = Y * \phi^{-\alpha}$, which would be observed if we correct for inefficiencies. The equation to be estimated is:

$$Y^{hy} = Y * \phi^{-\alpha} = e^{\beta_0 + u} * \Pi_{i=1}^{5} X_i^{\beta_i} * \phi^{-\alpha} \quad (12)$$

Results of the estimation of equation 12 for 1989 are listed in *Table 5*. Estimates were made with the *r*estricted, $\phi_{CRS/VRS} \geq 0.7$, and the *unr*estricted data set.

In comparing the results of the restricted estimation with equation 11, we find that the corrected version of the Cobb-Douglas function is less labor efficient, but more energy and fuel efficient. The goodness of fit also improved slightly by output correction. However, this can be due to an increase of multicollinearity by adding the efficiency score to the equation.

4.7 The translog specification of the production function

In the search for the correct specification of a production function, several researchers use the translog specification. If we include the efficiency scores in the translog production function we obtain:

$$\begin{aligned} logY_i &= \alpha_0 + \sum_{i=1}^{n} \alpha_i logX_i + \sum_{i=1}^{n} \alpha_{ii}(logX_i)^2 + \\ &\quad \sum_{i=1}^{n}\sum_{i>j} \alpha_{ij} logX_i logX_j - \alpha_{\phi_{VRS}} log\phi_{VRS} \end{aligned} \quad (13)$$

Due to a lack of data, not all inputs were used here for estimation. An estimation with all five inputs would have led to a situation where twenty estimators would have

Table 4: Estimated elasticities of a restricted and unrestricted Cobb-Douglas production function and a restricted and unrestricted 2SLS with the efficiency score in the instrument list for 1989 and 1992.

	Cobb-Douglas		2SLS	
$\beta_{i,89}$	unrestricted	restricted	unrestricted	restricted
β_0	1.5, 0.34	1.33, 0.38	1.5, 0.34	1.33, 0.38
β_L	0.51, 0.1	0.64, 0.14	0.51, 0.1	0.64, 0.14
β_E	0.03, 0.05	0.04, 0.05	0.03, 0.05	0.04, 0.05
β_F	0.09, 0.04	0.06, 0.05	0.09, 0.04	0.06, 0.05
β_R	0.07, 0.04	0.05, 0.05	0.07, 0.04	0.05, 0.05
β_K	0.36, 0.07	0.32, 0.08	0.36, 0.07	0.32, 0.08
n	100	72	100	72
Adjusted R^2	0.84	0.85	0.84	0.85

$\beta_{i,92}$	unrestricted	restricted	unrestricted	restricted
β_0	1.55, 0.5	1.35, 0.51	1.55, 0.5	1.35, 0.51
β_L	0.8, 0.12	0.84, 0.12	0.8, 0.12	0.84, 0.12
β_E	0.07, 0.06	0.08, 0.06	0.07, 0.06	0.08, 0.06
β_F	-0.01, 0.05	0.02, 0.05	-0.01, 0.05	0.02, 0.05
β_R	-0.01, 0.05	0.05, 0.05	-0.01, 0.05	0.05, 0.05
β_K	0.43, 0.07	0.43, 0.08	0.43, 0.07	0.43, 0.08
n	104	101	104	101
Adjusted R^2	0.83	0.84	0.83	0.84

Table 5: Estimated elasticities of equation 12 with restricted and unrestricted data for 1989.

ϕ	$\beta_0, SE\beta_0$	$\beta_L, SE\beta_L$	$\beta_E, SE\beta_E$	$\beta_F, SE\beta_F$	$\beta_R, SE\beta_R$
$\phi unrv_{RS}$	1.46, 0.33	0.44, 0.1	0.07, 0.05	0.14, 0.04	0.03, 0.04
ϕrv_{RS}	1.3, .38	0.57, 0.14	0.08, 0.05	0.12, 0.5	-0.01, 0.05
$\phi unrc_{RS}$	1.44, 0.32	0.42, 0.1	0.08, 0.05	0.17, 0.04	0.01, 0.04
ϕrc_{RS}	1.35,0.37	0.56, 0.14	0.09, 0.05	0.13, 0.05	-0.01, 0.05

ϕ	$\beta_K, SE\beta_K$	$\alpha, SE\alpha$	n	Adjusted R^2	F-Prob
$\phi unrv_{RS}$	0.37, 0.07	0.81, 0.29	99	0.85	0.0000
ϕrv_{RS}	0.33, 0.08	1.2, 0.47	71	0.86	0.0000
$\phi unrc_{RS}$	0.37, 0.07	1.28, 0.34	99	0.86	0.0000
ϕrc_{RS}	0.32, 0.08	1.45, 0.46	71	0.86	0.0000

to be estimated with less than hundred observations. For this reason, equation 13 was estimated with L, F, K only.

The estimators of equation 13 are not consistent with the observation made with the Cobb-Douglas production function, L, namely, enters in the translog equation negative, but it is not significantly different from zero. Correction for inefficiency, $\alpha_{\phi_{VRS}} \geq 0$, does not lead to great differences in the estimated equation (*Table 6*). Restriction of the data set brings about larger differences in the estimators. Cross elasticities in the equation with $\alpha_{\phi_{VRS}} \geq 0$ are significantly different from zero in the unrestricted case. For all other estimators, no such pattern could be observed. Removing the outliers by data restriction, the coefficients of the estimated multiple regression change considerably. It seems that there are not enough observations to estimate equation 13 consistently. Also, the large degree of multicollinearity may account for this instability of the specified model.

Table 6: Estimated elasticities of a translog production function, equation 13, with restricted and unrestricted data in corrected and uncorrected form for 1989.

	unrestricted		restricted	
α	$\alpha_{\phi_{VRS}} = 0$	$\alpha_{\phi_{VRS}} \geq 0$	$\alpha_{\phi_{VRS}} = 0$	$\alpha_{\phi_{VRS}} \geq 0$
α_0	0.76, 1.6	0.69, 1,54	-2.63, 2.94	-2.99, 2.82
α_L	-0.33, 0.71	-0.19, 0.68	-0.14, 1.4	-0.44, 1.351
α_F	0.61, 0.3	0.6, 0.29	1.01, 0.4	1.02, 0.38
α_K	0.73, 0.58	0.67, 0.56	1.08, 0.75	1.4, 0.72
α_{LL}	0.12, 0.15	0.07, 0.15	-0.04, 0.24	-0.07, 0.23
α_{FF}	0.04, 0.02	0.04, 0.02	0.03, 0.03	0.03, 0.03
α_{KK}	-0.15, 0.09	-0.18, 0.09	-0.24, 0.12	-0.28, 0.11
α_{LF}	-0.34, 0.13	-.37, 0.13	-0.36, 0.19	-0.36, 0.18
α_{LK}	0.24, 0.22	0.3, 0.22	0.44, 0.28	0.53, 0.28
α_{FK}	0.1, 0.06	0.13, 0.06	0.09, 0.08	0.09, 0.08
$\alpha_{\phi_{VRS}}$	0	0.34, 0.13	0	1.09, 0.39
n	108	106	72	71
$adj R^2$	0.85	0.86	0.85	0.86
F-Prob	0.0000	0.0000	0.0000	0.0000

The task of explaining the production decline was not undertaken due to the fact that the published ruble/dollar exchange rates did not reflect economic reality and led to odd results. Additionally, two observations at one time would not be sufficient to use panel data techniques.

5 Discussion

DEA results proved to be useful in the following ways:

- ranking enterprises according to their efficiency scores;
- identifying the efficient frontier of enterprise categories;

- quantifying scale inefficiencies;
- identifying outliers; and
- specifying production functions.

The DEA program was programmed in such a way that any given enterprise can be compared with its peers. Peers, in this context, are enterprises which form the efficient frontier. Inefficient $DMUs$ are then compared to these peers. It is especially important to reach a "fair" ranking of $DMUs$, which allows us to cluster enterprises, not only according to their efficiency score, but also according to their peers given a certain output category. DEA compares enterprise of a single enterprise category. Enterprises of a certain input/output category do not change efficiency scores of other input/output categories when running the computation with a data set which comprises all enterprise categories.

DEA constructs a production frontier and measures efficiency relative to the constructed frontier. Subject to certain assumptions about the structure of the production technology, it envelops the data as tight as possible. Enterprises which are fully efficient, $\phi = 1$, form the efficient frontier. In the CRS setup the efficiency frontier can be calculated by a linear transformation of the efficient enterprise(s). In a theoretical 3-D representation, the envelope has the form of a cone. In the VRS setup, convex combinations of the efficient enterprises form the efficient frontier — a convex hull. In micro-economic terminology, the efficient frontier is the best proxy for the production possibility set. In this way, the DEA gives us the direct production possibility set in a multiple input/output framework.

A shortcoming of DEA is that it is not a stochastic concept. Differences in management decisions and environmental circumstances causes enterprises to deviate from the production possibility set. What is interpreted as a residual in an econometric framework, is interpreted as inefficiency in a DEA framework. Inefficiencies calculated via DEA are not interpreted as a stochastic random variable, whereas residuals from OLS represent disturbances, left out factors, efficiency differences, functional form discrepancies, and errors of measurement. Econometric models measure the distance of an enterprise to the fitted line by OLS. In contrast, in a DEA framework the distance of the enterprise to the practical production possibility frontier is measured using a LP program. However, deviations from the production frontier might not be entirely under the control of the DMU being studied. An unusually high number of random equipment failures, or simply bad weather, appear to the analyst as inefficiency. Additionally, any error or imperfection in the specification of the model could translate into increased inefficiency measures.

In applying DEA, one also avoids the fundamental problem, that with OLS one cannot really treat the right hand variables as independent variables. The inputs are not under the control of the researcher but are chosen by the producers themselves.[5] Economics is not a scientific experiment, although for the data at hand one could actually argue about the planned economy fulfilling this criterium.

Economics of scale is a very important issue in economic analysis and usually finds its expression in the production function. If the sum of the exponents of the

[5]For a more detailed discussion of these problems, see Griliches and Mairesse (1995).

Cobb-Douglas production function is larger than one, one is confronted with increasing returns to scale production technology. The estimated production function for the Siberian lespromhozes also shows increasing returns to scale technology. However, scale inefficiency scores do not indicate any correlation of scale inefficiency with the size of output. This weak correlation could also be due to the fact that there is no linear relationship. By plotting scale inefficiency against output in both physical and financial units in pooled and unpooled form, no indication of any specific functional form was detected. The picture was rather stochastic. Nevertheless, it was noticed that there were always some absolute "stars" within each enterprise category which were usually very large enterprises working with high productive western technology. These enterprises were fully VRS and CRS efficient. There were always downward sloping regression coefficients of regressions explaining scale inefficiencies with the size of output. This observation is consistent with increasing returns to scale Cobb-Douglas technology. Returns to scale are more pronounced in the wood-working industry. Larger producers in the wood-working industry were more efficient and productive than small producers. Statistical analysis of branches in the wood-working industry, other than the lespromhozes, is not very sensible because there are too few enterprises to be analyzed. DEA, on the other hand, can be applied to such small data sets.

DEA proved to be helpful in identifying outliers. DEA stands and falls with data quality but, at the same time, it is a very useful tool to analyze data quality. It is not a great secret that one of the reasons of the sharp output decline of almost all transition economies was that production data from enterprises were not reported correctly to the statistical organs. A working system of inter-enterprise coordination of cheating was established at that time. For the estimation of a production function of the Siberian forest industry, it was important to exclude enterprises which had incredibly high or low productivity. Such outliers can easily be identified by DEA. One faces either the situation where one "super-efficient" enterprise dominates the rest of the enterprises, or a number of very inefficient enterprises are present in the data set to be analyzed. In forestry terminology, one can speak of a positive or negative selection process. In the first case, one needs to eliminate the "super-efficient" enterprise and rerun the program. In the second case, one only needs to restrict the data set to be further analyzed to a certain efficiency level. Another strategy of identifying outliers is to use an engineering approach. These are simple mathematical models which predict the practical labor and energy inputs for a given output. In these models, the inputs are adjusted for a number of environmental and geomorphological parameters. DEA and the engineering approach showed similar results which are not presented in this paper.

In the search for the correct specification of a production function with the limited and uncertain data at hand, several different approaches were used. Some of these approaches are not standard practice and need to be discussed or even dismissed. One strategy was to use a Cobb-Douglas specification. Outliers were removed from the data set by restricting the $DMUs$ to be analyzed to a certain efficiency level. No "positive" or "super-efficient" outliers were detected. The calculation of a 2SLS with the efficiency score in the set of instruments virtually did not change the estimated elasticities of the Cobb-Douglas production function. From the production function, it can be concluded that enterprises were more capital and labor efficient in 1992. At that time, the first wave of workers leaving the enterprises to work for the private sector, was already over and appeared in the analyzed data. Assets were also seriously evaluated in order to be "prepared" for the mass privatization in subsequent years. Another way to include the inefficiency scores was to directly use them in the set of explaining variables. This has the effect that the output is corrected for its inefficiency and is therefore moved closer to the efficient frontier. This has the effect that the elasticities for labor are smaller and the elasticities for electric energy and fuel use are larger compared to the Cobb-Douglas function. Unfortunately, there was no functional relationship between the efficiency scores and other external variables like average log-volume, average transportation distance, coefficient of utilization of basic machinery, and share of hardwoods processed and were, therefore, not used in a more elaborate model. Including such variables in such a model would, of course, have been very sensible.

The other functional form of the production function that was used is a translog specification, which usually fits data better. The translog equation was also estimated with the restricted and unrestricted data set. Additionally, it was estimated with and without the correcting efficiency scores like in the Cobb-Douglas case. It was hoped that, via this estimation, one could quantify the rates of substitution between the input variables. Cross-products of the input variables and the efficiency scores was not thought to be sensible and were, therefore, not included in the model estimation. The elasticity of labor always enters negative, although not significantly different from zero, translog production function. Generally, hardly any coefficient was statistically different from zero. It is believed that coefficients of the translog specification do not correspond to the true model due to the fact that the number of observations was not sufficient and due to the high degree of multicollinearity.

6 Conclusion

Transition has revealed large scale inefficiencies of industrial production in the Russian Federation. In comparing Russian technology to western technology, efficiency gaps are huge. Physical labor productivity is lower in Russia by a factor of 6 to 40. For example, the introduction of a one man operating harvester technology could replace 40 Russian chainsaw loggers. This simple fact will have large impacts on future labor markets and the economics of rural areas and cities that are dominated by forest industrial enterprises. But, also the competitive position of forest industries will dramatically change as soon as restructuring and technological upgrading will occur on a larger scale. Current results already show that productivity differences between western and Russian technology are large; although compared to the productivity of current western technology,the efficiency gap within Russia is still rather small. It is expected that new technology combined with a significantly changed demand structure for Russian forest products will completely change the geography and structure of the Russian forest sector. The analysis revealed that the technological superiority and the geographic location are the main determinants of economic success.

Due to the fact that economies of scale became more pronounced during transition, it is expected that, at least on the enterprise level, concentration processes will force many small and marginal forest enterprises out of the market. The possibilities to economically salvage communities that are dependent on one forest enterprise look rather bleak. The most limiting factor of concentration in the woodworking industry is wood supply. Already today, large woodworking complexes face serious wood shortages. The gradual breakdown of the transportation infrastructure aggrevates this situation.

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