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Alexander Schiersch

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German Institute for Economic Research
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Tel. +49 (30) 897 89-0
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Inefficiency in the German Mechanical Engineering Sector*

Alexander Schiersch†

Abstract

This paper aims to examine the relative efficiency of German engineering firms using a sample of roughly 23,000 observations between 1995 and 2004. As these firms had been successful in the examination period in terms of output- and export-growth, it is expected that a majority of firms is operating quite efficiently and that the density of efficiency scores is skewed to the left. Moreover, as the German engineering industry is dominated by medium sized firms, the question arises whether these firms are the most efficient ones. Finally an increasing efficiency gap between size classes over time is important since that would be a signal for a structural problem within the industry. The analysis - using recently developed DEA methods like bootstrapping or outlier detection - contradicts the two first expectations. The firms proved to operate quite inefficiently with an overall mean of 0.69, and efficiency differs significantly with firm size whereas medium sized firms being on average the least efficient ones. When looking at changes in efficiency over time, we find a decreasing efficiency gap between size classes.

JEL Codes: C14, L60

Keywords: DEA, German engineering firms

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† DIW Berlin, Department of Industry, Innovation and Service, Mohrenstraße 58, 10117 Berlin, aschiersch@diw.de tel.: +49-30-89789-262, fax.: +49-30-89789-103

I Introduction

Germany is known to be the worlds export champion since 2003 and its growth and prosperity has become heavily depending on its export industries.[1] Between 1995 and 2005 the share of exports on GDP rose from 22 to roughly 40 percent (Statistisches Bundesamt, 2006a), while the share of export depending employment rose from 15.6 to 21.4 percent or 8.3 Million jobs (Mohr, 2008). In terms of export values the most important sectors were the automotive industry, the mechanical engineering industry and the chemical industry, which account, according to the GENESIS data base of the German Federal Statistic Office, for 19.3, 14.4 and 13.0 percent of overall industry exports in 2004. With respect to employment the engineering industry is even more important providing almost 1 Mill. jobs in 2004, while the automotive and the chemical industry offered 863,00 and 446,000 jobs (Statistisches Bundesamt, 2006b).

The engineering industry is therefore referred to be a pillar of the German industry and its prosperity is of importance for the whole economy. It was successful in increasing its overall output by roughly 25 percent in the sample period while its exports increased by more than 50 percent from 62.8 to 106.5 Bill. Euros as depicted in Figure 1. In terms of gross value added it was also the leading sector within the German industry, accounting for 15 percent or 67.7 Bill. Euros in 2004 (Statistisches Bundesamt, 2009). However, beside these quite impressive figures little is known about the production efficiency of these firms, given that one would expect efficient operations to be an important contributing factor to this success. Therefore, this paper examines the efficiency of Germanys engineering firms focusing on three topics. Firstly, it is analyzed to what extend the success is due to highly efficient operations. Secondly, the relationship between firm size and efficiency is evaluated against the background of an industry that is dominated by medium sized firms. Finally, changes in efficiency over time are then measured in order to identify possible structural changes within the industry.

The remaining paper is organized as follows. Previous research findings and the hypotheses are presented in section II. Section III provides the reader with a short overview of the methodology. The fourth section is devoted to the description of the data and the employed variables. The results of the empirical analysis are presented in section V whereas section VI concludes.

[1] "Der deutsche Außenhandel hat für das Wirtschaftswachstum sowie den Arbeitsmarkt in Deutschland zentrale Bedeutung." (Statistisches Bundesamt, 2006a)

II Previous Research and Hypotheses

In theory, efficient productions are described by the most efficient input-output combinations of the production function. The production function in turn shows the technical or natural restriction in production. It also defines the production possibility set, containing all technically possible but inefficient production plans. In theory this area is of little interest as it is expected that profit maximizing firms always produce efficiently and do not waste resources.[2] Besides, we could further argue that in a competitive environment firms are forced to be efficient in order to survive and make enough profits to reinvest for being technically up to date. According to the above mentioned successful development of the German engineering industry and in line with economic theory it could be expected to find a majority of firms operating at an efficient level, i.e. with an efficiency score – scaled between zero and one – to be near one.

However, empirical studies examining efficiency in non-regulated industries found little evidence for average efficiency scores close to one. A recent paper by Badunenko (2008) found efficiency in the German chemical industry to be on average between 0.70 and 0.77. According to Badunenko et al. (2008), average efficiency in the German industrial sector is around 0.63, while Funke and Rahn (2002) found average efficiency in the West-German engineering industry to be between 0.83 and 0.85. Only little is known about efficiency in non-regulated industries in other European countries. The average efficiency of the Spanish industry oscillates around 0.76 according to Gumbau-Albert and Maudos (2002). Martin-Marcos and Suarez-Galvez (2000), using different classification, found average efficiency scores of Spanish engineering firms ranging from 0.64 to 0.72. The average efficiency of small and medium size companies (SME) in the Chilean Industry was around 0.65 according to Alvarez and Crespi (2003), while that of the engineering industry was 0.71.

One has to take into consideration when trying to compare these results, that the studies used different approaches, ranging from a fixed effect model (Badunenko et al., 2008) to stochastic frontier models (Funke und Rahn, 2002; Gumbau-Albert and Maudos, 2002; Martin-Marcos and Suarez-Galvez, 2000) and to the non-parametric data envelopment analysis (Badunenko, 2008; Alvarez and Crespi, 2003). Yet all approaches try to approximate a production function (called frontier) to measure efficiency. Moreover, the database as well as the defined and applied inputs and outputs differ between these studies. However, no study found average efficiency scores close to one. But even if the literature does not support the expectation of an average efficiency close to one, the afore mentioned prosperity of German engineering firms leads to the expectation that the majority of these firms operate rather close

2 The reader is referred to Varian (2001) and Figure 2 in Appendix A.

to the frontier. As there is always a minority of firms leaving the market it can also be expected to find a density of efficiency scores that is skewed to the left with a majority of firms operating quite efficiently while a minority does not. Such skewness seems also reasonable if one takes into account that the probability of survival ought to fall with increasing inefficiency and thus with efficiency scores below the mean. This leads to the first hypotheses:

Hypothesis 1: *(a)* A majority of the German engineering firms is operating fairly efficient.
(b) The density of the efficiency of engineering firms is skewed to the left.

Besides pure efficiency the question arises if efficiency significantly differs across company sizes and if larger companies are more efficient than smaller ones. Looking at the structure of the German engineering industry this question is a crucial one since there is an industry with many medium sized firms, so called “Mittelständlern”, and the widespread notion is that these firms are the heart and backbone of the industry. By 2004 they accounted for 53 percent of all firms and 46 percent of all jobs in the sector. In contrast just 5 percent of the firms are large ones (LEs)[3] but they accounted for 45 percent of all jobs in the same year. The small and micro companies finally provide 9 percent of all jobs and account for 42 percent of all companies. The trend, at least in terms of number of firms is in favor for the SMEs.[4] They increased by 6.5 percent while the number of employees was stable between 1995 and 2004. At the same time the number of LEs as well as the number of jobs provided by these firms felt by 18 and 17 percent. However, the SMEs account for less than 48 percent of gross production value in 2004 (Statistisches Bundesamt, 2006b).

Thus, this relationship between size and efficiency needs a closer look. The literature is ambiguous in this respect. On the one side it is argued that financial restrictions for small companies result in a lower efficiency. Furthermore larger companies are able to exploit economies of scale or scope and are therefore more efficient (Kumar 2003). On the other hand, following Leibenstein (1966) it is more difficult to keep all units within a large firm coordinated. Due to supervision efforts and a more hierarchical structure, efficiency in large companies may fall. According to Agell (2004), employees in small companies are more intrinsically motivated than the ones in big companies. These factors combined with a more flexible structure, shorter communication channels and a faster decision making process could enhance efficiency of small firms.

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[3] Here large enterprises (LE) are defined as companies with more than 500 employees.

[4] These are firms with less then 500 and more than 10 employees. The turnover as second criteria is supposed to be larger than 1 Mill. Euros but not more than 50. Mill Euros p.a.

In contrast, empirical studies such as Gumbau-Albert and Maudos (2002) found a positive relationship between size and efficiency, taking turn over as a proxy for size. Defining size by the number of employees, roughly the same is true for the German chemical industry as Badunenko (2008) revealed. Also taking the number of employees to define size, Alvarez and Crespi (2003) found differences between size classes, whereas micro firms are found to be more efficient than small ones, but less efficient than medium sized firms. This result is supported by the findings of Prùša (2009) who analyzed the efficiency and size of the Czech SME's. Chow and Fung (1997), examining the efficiency and size relation in Shanghai's manufacturing industries found that efficiency is increasing with firm size, but that the smallest enterprises have a higher efficiency than medium sized firms, while large companies are the most efficient ones on average. Finally Badunenko et al. (2008) found a strict but negative relation between size and efficiency analyzing data of German manufacturing industries. Thus, there are findings in favor of small firms, medium sized firms and large firms. But a closer look also reveals that all studies that found medium sized firms to be the most efficient ones did not include large firms, while those with large firms in the sample usually found the latter to be most efficient. This leads to the second hypotheses:

Hypothesis 2: *(a)* There are significant differences in efficiency between size classes.
(b) On average, the efficiency increases with firm size.

When finally looking at the changes in efficiency over time the questions arises if the least efficient size classes catch up to the most efficient ones? A complete catch up however is not reasonable, since that would violate the second hypotheses. If catching up took place it should therefore be in line with the ranking between the groups, while the gap in efficiency should be subject to changes. On the other hand, if we see no catching up but the least efficient size classes to further fall behind, the industry would face a structural problem. Hence, the last step of the analysis will answer the question:

Research Question: Did the least efficient size classes reduced the efficiency gap to the most efficient ones, or did the gap become larger?

III Methodology

For the present analysis a nonparametric frontier approach was adopted to estimate Farrell's technical efficiency (Farrell, 1957), basically using the idea of a production function and its production possibility set as visualized in Figure 2. In general, the fields of research that apply a nonparametric approach, especially the data envelopment analysis (DEA), are enormous as shown by Tavares (2002). The foundation of this success was created almost fifty years ago by the works of Koopmans (1951), Debreu (1951), Farrell (1957) and Shephard (1970), to name the most important ones. Moreover, it has to be stated that Deprins et al. (1984) invented the practical approach to measure efficiency using a free disposal hull (FDH), while the data envelopment analysis (DEA) became popular by the work of Charnes et al. (1978). To make the approaches actually applicable the statistical properties of their estimators are crucial. Here Banker (1993) and Kneip et al. (2003, 2008) as well as Simar and Wilson (2000b, 2002) have done the basic research.

There are several reasons for the preference of nonparametric analysis in econometric research. One of them is the fact that no assumptions regarding the functional form of the production function are necessary.[5] The actual measurement utilizes a best practice frontier based on actual observations. This frontier itself is defined by the production set

$$\Psi = \left\{ (x,y) \in \Re_+^{p+q} \middle| x \quad can \quad produce \quad y \right\} ,$$

where $x \in \Re_+^p$ contains a set of p inputs and $y \in \Re_+^q$ contains a set of q outputs. Since an input orientated approach will be adopted the input requirement set for all $y \in \Psi$ is described by $C(y) = \left\{ x \in \Re_+^p \middle| (x,y) \in \Psi \right\}$ and thus the frontier is finally defined by

$$\partial C(y) = \left\{ x \middle| x \in C(y), \theta \quad x \notin C(y) \forall \quad 0 < \theta < 1 \right\}.$$

This frontier can be seen as an empirical production function derived out of real input-output combinations. The input oriented technical efficiency by Farrell for firm with an observed combination of outputs and inputs (x_0, y_0) based on the frontier above is given by

$$\theta(x_0, y_0) = \inf\left\{ \theta \quad \middle| \theta x_0 \in C(y_0) \right\} = \inf\left\{ \theta \middle| (\theta x_0, y_0) \in \Psi \right\},$$

whereas $\theta(x_0, y_0)$ is a radial measure, taking values between zero and one. Consequently, a company is considered to be efficient if it lies exactly on the frontier and hence its θ takes the value of one. In contrast, if $\theta(x_0, y_0)$ is below one (e.g. $\theta = 0.7$), the company would need to reduce the amount of assembled inputs by $1-\theta$ percent in order to operate efficiently.

Of course the real production set is unknown. Typically there is just a sample of observations $\Theta_N = \left\{ (x_i, y_i), i \ = \ 1, \ldots, n \right\}$ and Ψ needs to be estimated. This can be done either by using the free disposal hull method or by applying DEA, which was done in this analysis. Depending on the assumed returns to scale, the production set has a convex or conical hull.

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5 The assumptions that form the basis of these nonparametric models are rather rudimental, affecting mathematic questions like a closed input/output space etc. For further information on the assumptions see for instance Daraio and Simar (2007).

The DEA frontier under variable returns to scale (and therefore with a convex hull) is defined as follows:

$$\hat{\Psi}_{VRS}\left(\Theta_N\right)=\left\{\left(x,y\right)\in\Re_+^{p+q}\middle| y\leq\sum_{i=1}^{n}\gamma_i y_i, x\geq\sum_{i=1}^{n}\gamma_i x_i, \sum_{i=1}^{n}\gamma_i=1, \gamma_i\geq 0\forall i=1,\ldots,n\right\},$$

and the technical efficiency can be calculated by solving the subsequent linear program

$$\hat{\theta}_{VRS}=\min\left\{\theta>0\middle| \; y\leq\sum_{i=1}^{n}\gamma_i y_i, \quad \theta x\geq\sum_{i=1}^{n}\gamma_i x_i, \sum_{i=1}^{n}\gamma_i=1, \gamma_i\geq 0\forall i=1,\ldots,n\right\}.$$

A major concern in econometric analysis is the consistency of the estimators. Within this framework the estimator is always consistent under the assumption of variable returns to scale (VRS), although it is not efficient if the production set exhibits constant (CRS) or non-increasing returns (NIRS) to scale (Simar and Wilson, 2002). On the other hand, if Ψ exhibits variable returns to scale and the model assumes constant or non-increasing returns to scale, both $\hat{\theta}_{CRS}$ and $\hat{\theta}_{NIRS}$ are inconsistent. Therefore a test is needed to make sure which scale characteristic is appropriate. Typical tests as the Kolmogorov-Smirnov test perform rather poorly within the DEA context so that a new test was defined by Simar and Wilson (2002) to examine the scale characteristics of the frontier. That one is used in this study.

Another important issue is the potential bias of DEA-estimators. This bias traces back to the fact that the efficiency of a firm is measured by its position within the production set compared to the frontier of this production set. Since the latter is estimated itself based on a limited sample, $\hat{\Psi}_{DEA}$ is a subset of the unknown production set $\left(\hat{\Psi}_{DEA}\subseteq\Psi\right)$ by construction and therefore $\partial\hat{C}_{DEA}(y)$ is inward-biased compared to $\partial C_{DEA}(y)$. Consequently, the technical efficiency of a firm is potentially upward-biased $\left(\theta_{VRS}\leq\hat{\theta}_{VRS}\right)$ or in other words too optimistic (Simar and Wilson, 2005). Hence, it is necessary to calculate bias-corrected estimates which can be done by bootstrapping. Unfortunately, the naive bootstrap method leads to inconsistent estimates if applied to DEA-estimators since they are bounded. Nevertheless, calculating bias corrected estimates is possible and was done in the present survey (see Simar and Wilson 1998, 2000a, 2000b and Kneip et al. 2008).

Nonparametric analyses are also "cursed" as some scientists put it. This "curse" is related to the convergence of estimators and their dimensionality. Within the DEA, estimators converge at a rate of $n^{2/p+q+1}$. Thus, as the number of inputs and outputs applied in the calculation increases, the rate of convergence decreases. A further problem appears with increasing dimensions. As shown by Wheelock and Wilson (2003) the number of efficient firms, i.e. of DMUs that lie at the frontier, increases with a rising number of dimensions. This is not surprising looking at the way the frontier is designed. The number of defined inputs and outputs should therefore be limited.

Another point to have in mind in DEA is the sensitivity towards outliers. This problem can be overcome by another recently developed approach, the semi-parametric outlier detection method by Simar (2003). The basic idea is the estimation of an order-m frontier (Cazals et al., 2002) which is not enveloping all observations and thus accounts for possible outliers and noise. Using several levels of m and α one is able to choose a reasonable combination of both and the tabled results are then used to decide which of the potential outliers are true outliers by looking at each of them individually. This is especially true for potential outliers on the lower or upper end of the frontier, because they can possibly be labeled as outliers due to the limited number of observations in their neighborhood.[6]

Finally, it is necessary to decide whether one should use a common frontier or not. Utilizing a common frontier assumes a stable technology over the examination period. The impact of this assumption is as critical as the assumption concerning the economies of scale. An erroneous assumption regarding the stability of technology could result in inconsistent efficiency scores, since they would contain inefficiencies regarding technologies that did not exist in specific periods.[7] An easy way to avoid such distortion is the construction of yearly frontiers, which was done in this survey.

In order to derive consistent estimates the actual calculations will have to follow a strict procedure. According to the theoretical remarks the first step is the detection of outliers, which will be done by applying the already mentioned outlier detection method. After controlling for outliers the scale assumption needs to be outlined and tested using the described return to scale test. Finally, by constructing yearly frontiers and applying the bootstrap method, bias corrected efficiency scores are obtained and the hypotheses can be tested.

IV Data

The study uses data from the German Cost Structure Census of manufacturing (CSC) for the period 1995 to 2004. This sample is gathered by the German Federal Statistic office and firms are obliged to deliver the requested data. All companies with more than 500 employees are always part of the sample. In addition a representative set of smaller companies is also included as a random sub sample.

Since it is the efficiency of engineering firms that is of interest, only data of this sector are used, giving us a sample of 23,591 observations between 1995 and 2004 with a wide range of

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6 The approach is very intuitive and easy to implement based on the already published MATLAB code by Simar (2003). The interested reader is referred to it for more information.

7 The reader is referred to Grosskopf (1993) for more information on changes in efficiency over time and technological changes.

characteristics.[8] This large set of information is generally appreciable but the chosen dimension should not be too high because of the already mentioned "curse". Hence, in order to avoid implausible estimates the characteristics were summed up to create five factors. The first one is output, which is basically the gross production value adjusted by all revenues that have nothing to do with the core business of an engineering firm, such as turnover out of 'other activities' or 'trading goods'. These revenues were excluded since they have no explanatory power in terms of a production function.

The model contains the additional input factors: 'material', 'capital', 'labor' and 'others'. The factor 'material' includes all materials and preliminary products as well as energy. The 'capital' contains first of all interest and amortization. Moreover, rental and leasing expenditures need to be taken into account. Since a company could also buy a machine or a building rather than rent it, 'capital' also include these expenses. The third input factor 'labor' is also made up of several characteristics. It entails all wages including the social insurance contributions that companies must pay. In addition all social benefits (e.g. employee pensions) guaranteed by firms beyond legal requirements are summed up in the factor. The remaining costs like repair, installation etc. are put into the factor 'others'. After creating these new factors their values are deflated.

However, constructing inputs and outputs using monetary units needs further discussion. The efficiency measure described above arises from a comparison of an observed input-output combination and its corresponding pair on the best practice frontier. The appropriate way to do that is by looking at physical units in the production process. Unfortunately the sample contains no physical information but monetary value data. When applying the above mentioned methods on this data the calculated efficiency scores would measure the distance to a frontier that is defined by data with allocative and technical information. Unfortunately, we can not conclude whether the measured inefficiency is caused by inefficiencies in the production process or whether it is due to allocative inefficiencies. Since no information on input prices or input units is given it is not possible to derive the allocative and technical efficiency separately. However, by assuming that input prices do not differ between firms due to market prices and competition on the input markets, having allocative information just means that we have a linear transformation of input quantities. The result is therefore just a shift of all observations within the production possibility set, whereas this shift is equal for all observations due to the identical input prices and consequently also for the frontier.

8 Almost all characteristics entail information in monetary form. In this study only the monetary informations are used and summed up. The only exception is the number of employees, but these are not used as input factor in the calculation.

V Results

According to the above outlined procedure the analysis starts by detecting and removing outliers. In a first step all obvious errors are deleted, that is observations with zero inputs or outputs. The semi-automatic outlier detection method by Simar (2003) is applied thereafter on the remaining 22,131 observations. Roughly 2 percent of all meaningful observations are labeled as outliers and removed from the sample. The remaining 21,650 observations are quite constantly distributed over the years.[9] Based on this sample the actual analysis was conducted. The results of the returns to scale test show that the frontier in all years is characterized by variable returns to scale at p-values of zero.[10] Applying the assumption of variable returns to scale and constructing yearly frontiers, the bootstrap method is used to estimate bias-corrected efficiency scores to validate the first hypotheses.

As Figure 3 reveals, the majority of the firms are working at an efficiency level far below one. The mean as well as the median are roughly 0.69. Hence, the engineering firms are operating on average inefficiently, using about 31 percent more inputs than necessary. Furthermore in fifty percent of all observations the firms work at an efficiency level of 0.63 to 0.76, meaning that they use 24 to 37 percent more inputs than necessary. In just five percent of all cases firms have had an efficiency score above 0.86. In contrast, 20 percent of all observed efficiencies are between 0.63 and 0.52. In these cases firms used almost twice as many input as necessary. Also the form of the density is surprising: it is almost a normal distribution (with $\mu = 0.6944$ and $\sigma = 0.1088$) with nearly as many firms with efficiency scores below the mean as there are firms with efficiency scores above the mean.[11]

Thus, the hypothesis of German engineering firms working on average quite efficiently, that is *hypothesis 1(a)*, is rejected. The majority of engineering firms produces at an efficiency level of on average 0.69. The expectation of a density that is skewed to the left, hence *hypothesis 1(b),* is rejected by the results as well.

Besides efficiency the second hypotheses questions whether the efficiency of a firm increases on average with firm size. This is especially interesting as there is a widespread presumption in the German public that SME's, but especially the medium sized firms, are the backbone of German industrial success, in particular in the engineering industry. In a first step firms are separated by the number of employees, whereas the rather rough EU definition for

9 See Table 1 in Appendix B.

10 See Table 2 in Appendix B.

11 A test of normal distribution rejects the null hypothesis. The statement of "almost" just addresses the optical conformity between the probability density and the diagrammed density of the normal distribution (yellow line).

SMEs is extended according German Federal Statistic Office, creating six groups.[12] To illustrate possible differences in efficiency for each size, the empirical distribution functions of efficiency scores are drawn within one graph. Figure 4 shows that there are significant differences. The black curve, which pictures the efficiency scores of large firms with 1000 and more employees, dominates all other curves. Hence, within this group the number of firms with a rather high efficiency score is the highest and consequently the average efficiency of large firms is also higher than that of smaller firms. This becomes also obvious looking at the descriptive statistics in Table 3.

More importantly, even if large firms are the most efficient ones on average, the results in Figure 4 and Table 3 show that there is no straight relationship between size and efficiency. This becomes apparent when looking at the blue curve which contains the efficiency scores of the smallest companies. It dominates the curves (green and red) of the next size groups (50 – 99 E and 100 – 250 E).[13] Hence, small companies are on average more efficient than the next larger ones. It seems as if the relationship between size and efficiency is rather u-shaped than straight and that large as well as small companies are on average more efficient than the medium sized firms.[14] The discovered differences are furthermore statistically significant as the p-values of the applied bilateral Wilcoxon rank-sum tests in Table 5 show.

Another criterion commonly used with the number of employees to define firm size is the companies' turnover. In default of turn over, output is used in this study to classify the size of firms. In order to overcome the rather rough EU definition, the size classes are chosen so that the number of observations in each of the created classes is around 2400. This gives us nine instead of six classes and allows for a more diverse picture.[15] Figure 5 shows again the conditional empirical distribution functions of efficiency scores in each size class: It confirms the previous analysis according to which we observe significant differences. The suspected u-shape becomes even more pronounced. After a rather high median efficiency of 0.75, we observe a sharp drop to almost 0.65, followed by an increasing efficiency with higher output levels. Taking the median efficiency and the corresponding median output for each size class, the observed u-shaped relationship is visualized in Figure 6. As shown in Table 11, the u-

[12] The classes are defined as follows: 20-49 employees (E), 50-99 E, 100-249 E, 250-499 E, 500-999 E and 1000 and more employees (Statistisches Bundesamt, 2006b). The EU definition for SMEs with respect to size is as follows: <10 micro companies, <50 small enterprises, <250 medium sized enterprises.

[13] Of course there are efficient firms in each size class in every year as can be seen in Table 4 in Appendix B. The lower efficiency is therefore not just because of a frontier that is only defined by small and large companies.

[14] As depicted is Table 10, this holds true even if we look at it for each year individually.

[15] The classification in Mill Euros (y is used as a dummy for gross production value) is as follows: $y \leq 3$, $3 < y \leq 5$, $5 < y \leq 8$, $8 < y \leq 12$, $12 < y \leq 19$, $19 < y \leq 30$, $30 < y \leq 55$, $55 < y \leq 120$, $120 < y$.

shaped relationship still holds true when looking at the efficiency in each size class on a yearly basis. The corresponding tests for identically distributed efficiency scores support this finding as well.[16]

Thus, the *second hypothesis (a)* of significant differences in efficiency between large, medium sized and small companies can be confirmed but differently than expected. Even though large firms prove to be the most efficient ones, small ones are almost as efficient, while the medium sized firms are the least efficient. The relationship between size and efficiency is therefore more precisely described by a u-shape than by the assumed straight positive correlation as expected in *hypotheses 2(b)*.

Lastly the measured efficiencies are used to analyze the changes in efficiency over time. By looking at the efficiency scores in each year and size class we can answer the question if catching up occurred or if the least efficient classes further fall behind. In a first step we rank the size classes according to their efficiency in each year, as it is done in Table 8 and Table 9. Taking the first and the last three years as average, we see only minor changes.[17] The medium sized firms were not able to increase their ranking. Taking the number of employees as a proxy for size, they started with the worst ranks and still had these ranks in the last period. We just see a little shift such that the group with 100-249 employees started with the last ranking (6) and had the slightly better ranking (5) at the end. When we define size by turnover, the changes are also minor.

However, even if the efficiency order proves to be stable, the gap between the classes might have changed. By taking the large firms as benchmark we can measure that gap of each class to that benchmark. As shown in Figure 7, we see a stable structure between the classes. The least efficient classes always have the highest differences with a peak in 1998. In this year the gap ranged from 17.29 percent (50-99 employees) to 3.19 percent (500-999 employees). After 1998 the gap constantly decreased until 2003 with 2.27 percent (20-49 employees) to 8.78 percent (50-99 employees). Hence, within a time frame of five years a catching up took place. The same holds true when defining size by turnover, as can be seen in Table 11. Yet, its impact was not large enough to change the ranking between size classes as shown before. After 2003 the gap became larger again but not as much as in 1998.

Thus, we can positively answer the research question. The ranking between size groups stayed stable but the gap in efficiency was subject to changes. We observed no group falling behind and therefore but some catching up and the narrowing of the quite large gap of the late 1990's.

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[16] The results are tabled in Table 7 in Appendix B.

[17] A two year period would do just as well.

VI Conclusion

This paper analyses the efficiency of German engineering firms by making use of a large data set with more than 23,000 observations and applying recently developed DEA methods. As shown in the beginning, the engineering firms were economically successful within the examination period. They increased their output by around 25 percent while the export grew by roughly 50 percent to more than 100 Bill. Euros. It was expected that this economic success was based on highly efficient operations. Moreover, the differences between small, medium and large firms were analyzed. This is especially interesting in the case of the German engineering sector, since it is dominated by small and medium sized firms and the widespread notion is that these firms are the heart and backbone of the industry. Finally, it was analyzed whether the changes in efficiency over time increased or narrowed the expected gap in efficiency between size classes.

Firstly, the average efficiency of the firms – scaled between zero and one – was found to be 0.69. Hence, the average firm could produce the same output by using just 69 percent of the actual input. Given this average inefficiency of 31 percent, there is a lot potential for reorganization and restructuring in the German engineering industry. We can furthermore not conclude that the economic success was due to highly efficient operations of a majority of the firms. There need to be other factors than pure efficiency that drove that success.

With respect to the relationship between size and efficiency the analyses showed a slightly different picture than expected. The anticipated positive relationship between size and efficiency was confirmed by the results in a way that the largest and the second largest firms are found to be the most efficient ones on average. The smallest firms however are found to be almost as efficient. Thus, the actual results indicate a u-shaped relationship, finding micro and small firms to be more efficient than medium sized firms while the large firms are the most efficient ones. The medium sized firms are found to be the least efficient ones on average, regardless of the proxy used to define size. Again, although these firms are often economically successful, they showed the highest optimization potentials.

Finally it was looked at the differences in efficiency between size classes over time. As expected, the observed changes were not large enough to change the ranking of the size groups. The least efficient ones did not become the most efficient ones and so forth and the structure of the order of classes was found to be stable. Nevertheless, we saw some catching up. The gap between the most and the least efficient classes was the highest in 1998 with more than 17 percent. Until 2003 this gap narrowed to 8.8 percent. Even though that difference became larger again in 2004 we still can state some catching up. Yet, the fact that the ranking stayed stable over time indicates that there are some structural components, maybe the organizational differences between large, medium and small firms, that are given and responsible for the average differences in efficiency.

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Appendix A

Figure 1: Export and output of German engineering firms[18]

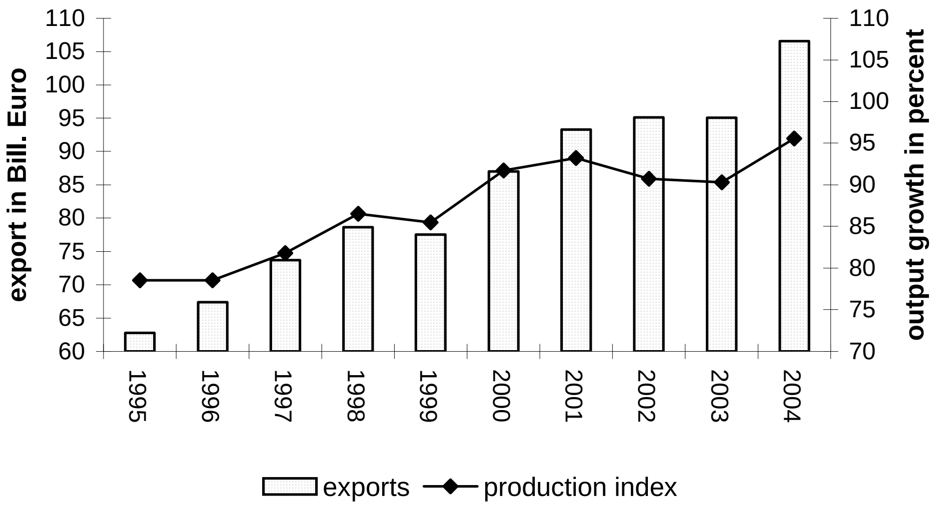
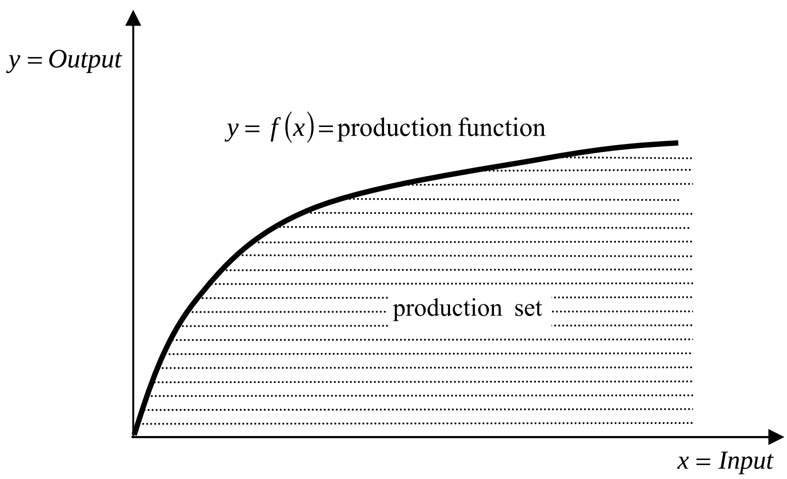


Figure 2: Production set and production function[19]



[18] Data are taken from the GENESIS data base of the German Federal Statistic Office.

[19] The figure was taken from Varian (2001).

Figure 3: Technical efficiency all years all periods[20]

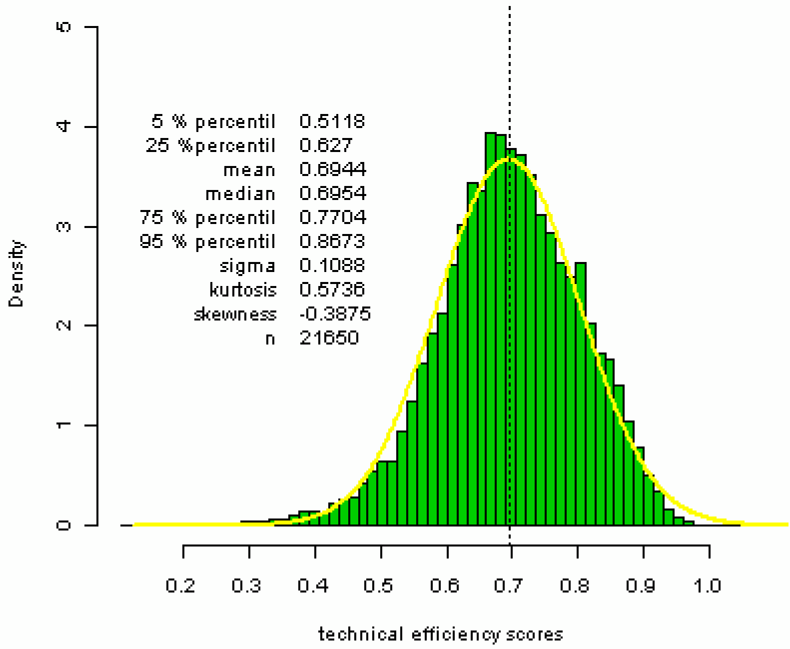
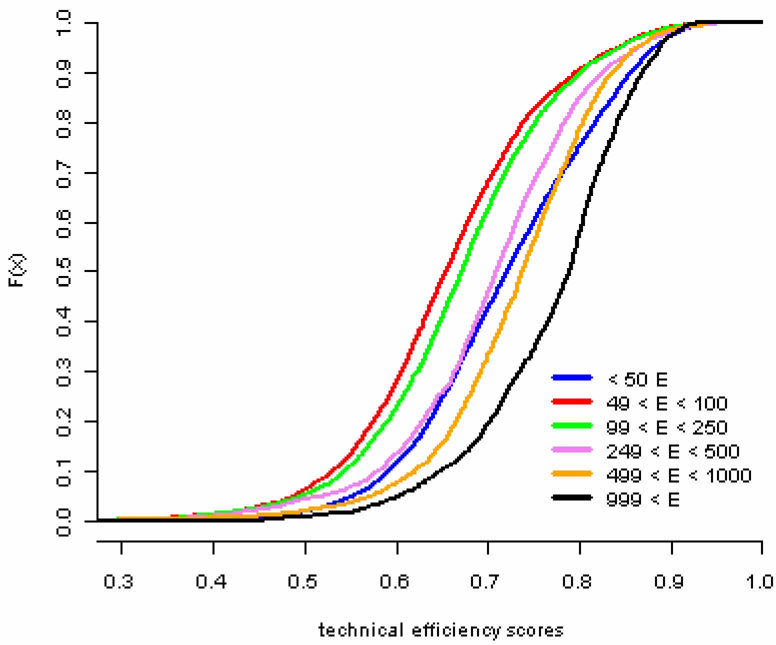


Figure 4: Empirical distribution function of efficiency scores for each size class, whereas size is defined by the number of employees



[20] The calculation was conducted by choosing a number of 1000 replications in the bootstrap procedure.

Figure 5: Empirical distribution function of efficiency scores for each size class, whereas size is defined by output level

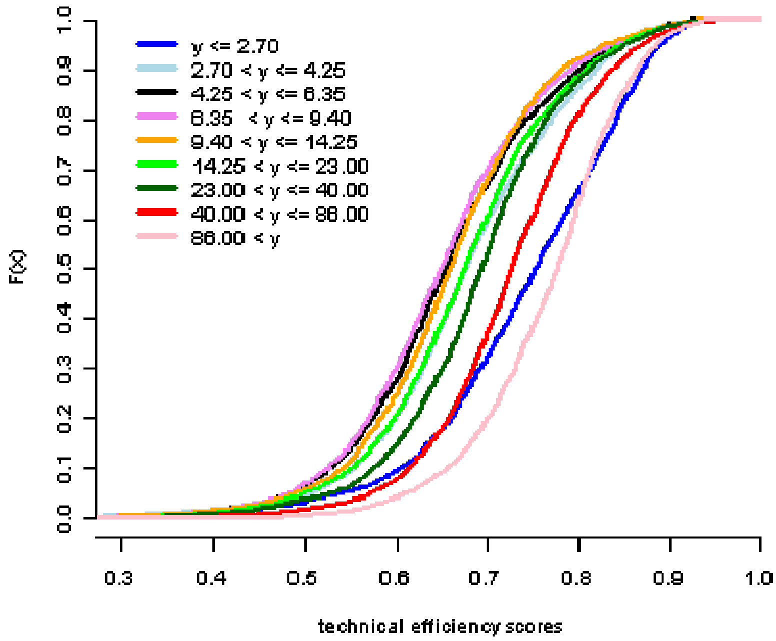


Figure 6: The median efficiency in each size class

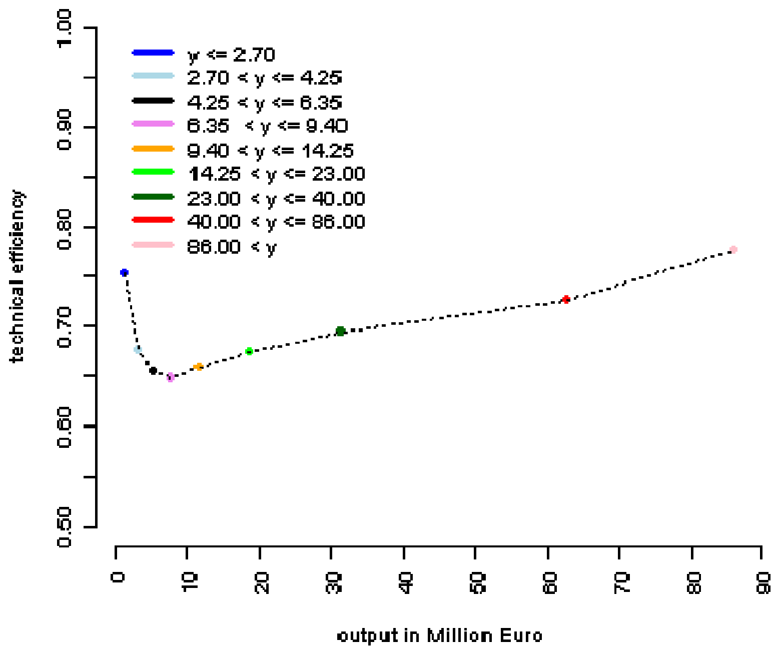
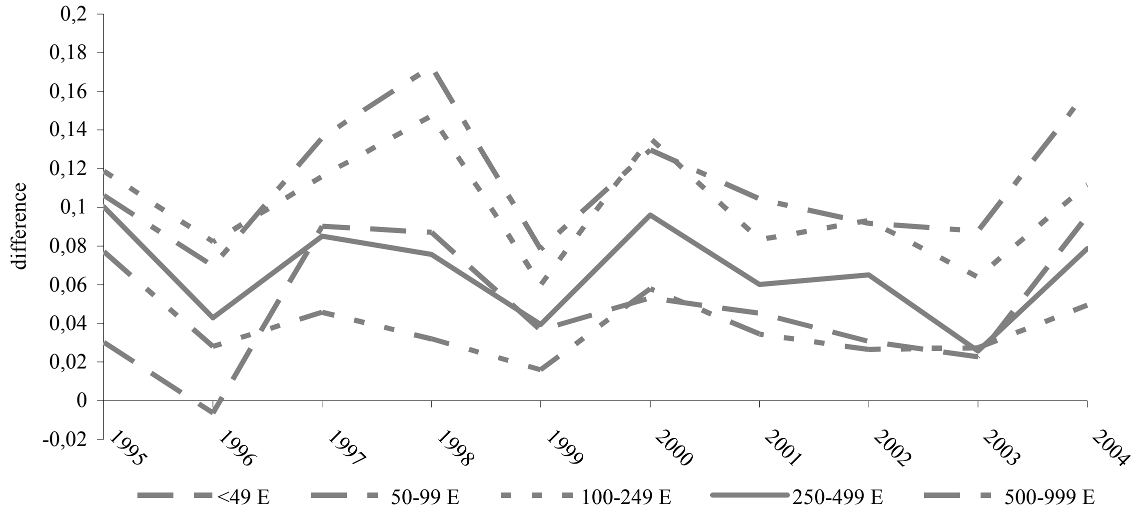


Figure 7: Gap in mean efficiency between sizes classes, whereas size is defined by the number of employees[21]



[21] The gap is measured by taking the mean efficiency of the largest firms (more than 1000 employees) as benchmark. The negative gap in 1996 for the smallest companies is because this class had the highest average efficiency score in this year and was therefore better than the chosen benchmark: the largest firms.

Appendix B

Table 1: Frequency of firm observations in the sample

year	number of observations	Share of all observations (percent)	cumulative number of observations	cumulative share of all observations (percent)
1995	2159	9.97%	2159	9.97%
1996	2127	9.82%	4286	19.80%
1997	2119	9.79%	6405	29.58%
1998	2025	9.35%	8430	38.94%
1999	2193	10.13%	10623	49.07%
2000	2207	10.19%	12830	59.26%
2001	2096	9.68%	14926	68.94%
2002	2027	9.36%	16953	78.30%
2003	2387	11.03%	19340	89.33%
2004	2310	10.67%	21650	100.00%
Total	21650	100.00%		

Table 2: Returns to scale test for each year

	years									
	1995	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**
n	2158	2127	2119	2025	2189	2207	2096	2025	2384	2308
p-value globally CRS	0	0	0	0	0	0	0	0	0	0
p-Value globally NIRS	0	0	0	0	0	0	0	0	0	0
RTS (1:VRS, 2:NIRS, 3:CRS)	1	1	1	1	1	1	1	1	1	1

Table 3: Efficiency in each size class, whereas size is defined by the number of employees

	size classes					
	0-49	**50-99**	**100-249**	**250-499**	**500-999**	**1000 ≤**
n	5484	4968	5401	2708	1777	1312
99er percentile	0.9208	0.9033	0.9033	0.9183	0.9166	0.9141
75er percentile	0.7994	0.7222	0.7348	0.7704	0.7918	0.8313
median	0.7205	0.654	0.6711	0.7087	0.7375	0.7893
mean	0.7209	0.6563	0.6688	0.7027	0.7295	0.7692
25er percentile	0.6502	0.5924	0.6075	0.6452	0.6789	0.7179
1er percentile	0.4527	0.3709	0.3754	0.3896	0.4413	0.5066
sigma	0.1038	0.1066	0.1061	0.1043	0.0943	0.0895
ranking	3	6	5	4	2	1

Table 4: Number of frontier observations in each size class in each year[22]

		years									
		1995	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**
size classes	**0-49**	62	55	46	43	47	47	45	50	59	50
	50-	12	17	19	9	18	17	19	17	15	17
	100-	12	16	16	17	16	9	22	22	15	18
	250-	9	8	12	10	16	15	8	10	8	12
	500-	8	9	12	11	5	5	8	10	9	7
	1000	26	17	25	25	27	33	27	26	23	22
	All	129	122	130	115	129	126	129	135	129	126

Table 5: p-values of the Wilcoxon – test for equally distributed efficiency scores between size classes, whereas size is defined by the number of employees

		size classes				
		50-99	**100-249**	**250-499**	**500-999**	**1000 ≤**
size classes	**0-49**	0	0	0	0	0
	50-99		0	0	0	0
	100-249			0	0	0
	250-499				0	0
	500-999					0

22 The frontier over the years is not defined by the same companies, since the construction of sub sample makes sure that firms with less than 500 employees are not part of that sample in successive sample periods.

Table 6: Efficiency in each size class, whereas size is defined by output level

		n	99er percentile	75er percentile	median	mean	25er percentile	1er percentile
size classes	**y≤2.70**	2404	0.9216	0.828	0.7524	0.7418	0.6775	0.3902
	2.70<y≤4.25	2411	0.9024	0.7524	0.677	0.6791	0.6161	0.3545
	4.25<y≤6.35	2418	0.899	0.7245	0.6547	0.6582	0.5915	0.3784
	6.35<y≤9.40	2386	0.906	0.7184	0.6489	0.6524	0.5858	0.3672
	9.40<y≤14.25	2405	0.9033	0.721	0.6592	0.6592	0.6013	0.3754
	14.25<y≤23.00	2394	0.9132	0.7375	0.6752	0.6755	0.6146	0.3929
	23.00<y≤40.00	2380	0.9083	0.7508	0.6944	0.6914	0.6361	0.4091
	40.00<y≤86.00	2392	0.9209	0.7832	0.7273	0.7251	0.672	0.4644
	86.00<y	2460	0.9246	0.8217	0.777	0.7656	0.7163	0.5245

Table 7: p-values of the Wilcoxon-test for equally distributed efficiency scores between size classes, whereas size is defined by output level

		size classes							
		2.70<y≤ 4.25	**4.25<y≤ 6.35**	**6.35<y≤ 9.40**	**9.40<y≤ 14.25**	**14.25<y ≤23.00**	**23.00<y ≤40.00**	**40.00<y ≤86.00**	**86.00<y**
size classes	**y≤2.70**	0	0	0	0	0	0	0	0
	2.70<y≤4.25		0	0	0	0.1728	0	0	0
	4.25<y≤6.35			0.0506	0.3100	0	0	0	0
	6.35<y≤9.40				0.0023	0	0	0	0
	9.40<y≤14.25					0	0	0	0
	14.25<y≤23.00						0	0	0
	23.00<y≤40.00							0	0
	40.00<y≤86.00								0

Table 8: ranking of size classes according to their mean efficiency scores, whereas size is defined by the number of employees[23]

ranking	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	**1995-1997**	**2002-2004**
<49 E	2	1	4	4	3	2	3	3	2	4	**2**	**3**
50-99 E	5	5	6	6	6	5	6	5	6	6	**5**	**6**
100-249 E	6	6	5	5	5	6	5	6	5	5	**6**	**5**
250-499 E	4	4	3	3	4	4	4	4	3	3	**4**	**3**
500-999 E	3	3	2	2	2	3	2	2	4	2	**3**	**3**
>1000 E	1	2	1	1	1	1	1	1	1	1	**1**	**1**

Table 9: ranking of size classes according to their mean efficiency scores, whereas size is defined by output level[24]

ranking	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	**1995-1997**	**2002-2004**
≤ 2.70	2	1	3	3	2	2	2	2	3	2	**2**	**2**
2.70-4.25	4	4	8	5	7	4	7	4	6	6	**5**	**5**
4.25-6.35	6	7	9	7	8	6	8	5	7	9	**7**	**7**
6.35-9.40	9	9	6	8	9	9	9	8	8	8	**8**	**8**
9.40-14.25	7	8	7	9	6	8	6	9	9	7	**7**	**8**
14.25-23.00	8	6	4	6	5	7	5	6	5	5	**6**	**5**
23.00-40.00	5	5	5	4	4	5	4	7	4	4	**5**	**5**
40.00-86.00	3	3	2	2	3	3	3	3	2	3	**3**	**3**
> 86.00	1	2	1	1	1	1	1	1	1	1	**1**	**1**

[23] The corresponding means are shown in Table 10.

[24] The corresponding means are shown in Table 11.

Table 10: Average efficiency in each size class for each year, whereas size is defined by the number of employees

			size classes						
			<49 E	**50-99 E**	**100-249 E**	**250-499 E**	**500-999 E**	**>1000 E**	**Total**
years	**1995**	n	511	507	543	251	197	150	2159
		Mean	0.744	0.668	0.6555	0.6738	0.6971	0.7742	0.6936
	1996	n	513	515	520	238	199	142	2127
		Mean	0.7575	0.6816	0.6689	0.7082	0.7231	0.7511	0.7083
	1997	n	542	487	506	265	186	133	2119
		Mean	0.6985	0.6526	0.6726	0.7036	0.743	0.7887	0.692
	1998	n	483	453	507	262	185	135	2025
		Mean	0.6828	0.597	0.6225	0.6943	0.738	0.7699	0.6608
	1999	n	575	497	525	286	175	135	2193
		Mean	0.7255	0.6836	0.7022	0.7226	0.746	0.762	0.7139
	2000	n	579	505	527	292	176	128	2207
		Mean	0.7328	0.6563	0.6502	0.6899	0.7282	0.786	0.6926
	2001	n	507	477	524	288	171	129	2096
		Mean	0.7078	0.6488	0.6698	0.6929	0.7186	0.7531	0.6865
	2002	n	491	471	506	279	156	124	2027
		Mean	0.7358	0.6748	0.6733	0.7014	0.74	0.7665	0.7035
	2003	n	661	522	634	278	171	121	2387
		Mean	0.7251	0.66	0.6839	0.7221	0.7205	0.7478	0.7004
	2004	n	622	534	609	269	161	115	2310
		Mean	0.7	0.6355	0.6835	0.7166	0.746	0.7953	0.6906

Table 11: Average efficiency in each size class for each year, whereas size is defined by output level

			size classes								
			≤ 2.70	**2.70-4.25**	**4.25-6.35**	**6.35-9.40**	**9.40-14.25**	**14.25-23.00**	**23.00-40.00**	**40.00-86.00**	**> 86.00**	**Total**
years	**1995**	n	252	251	254	248	237	235	228	220	234	2159
		Mean	0.7464	0.6894	0.671	0.6571	0.666	0.6631	0.685	0.7004	0.7646	0.6936
	1996	n	253	245	249	241	229	238	219	217	236	2127
		Mean	0.7613	0.715	0.6834	0.6704	0.6728	0.6837	0.7081	0.7274	0.7513	0.7083
	1997	n	284	225	207	249	210	228	239	247	230	2119
		Mean	0.7231	0.6403	0.6351	0.6652	0.6642	0.6867	0.6809	0.7311	0.7842	0.692
	1998	n	227	187	200	237	216	246	220	252	240	2025
		Mean	0.7134	0.6487	0.6068	0.6037	0.5964	0.6079	0.6489	0.7312	0.7714	0.6608
	1999	n	235	265	252	246	255	215	234	261	230	2193
		Mean	0.7508	0.6921	0.6773	0.664	0.6955	0.7184	0.7286	0.7428	0.7636	0.7139
	2000	n	216	269	263	239	252	224	231	253	260	2207
		Mean	0.7587	0.7031	0.6631	0.6435	0.644	0.6604	0.6737	0.7131	0.7734	0.6926
	2001	n	180	224	268	218	228	235	238	248	257	2096
		Mean	0.7466	0.6559	0.6503	0.6497	0.6563	0.6836	0.6837	0.7095	0.7497	0.6865
	2002	n	205	223	230	219	239	225	229	207	250	2027
		Mean	0.7633	0.6862	0.6849	0.6698	0.6655	0.6844	0.6785	0.7315	0.7698	0.7035
	2003	n	299	281	232	256	266	278	267	251	257	2387
		Mean	0.7322	0.6823	0.6698	0.6665	0.664	0.6853	0.7174	0.7323	0.7496	0.7004
	2004	n	253	241	263	233	273	270	275	236	266	2310
		Mean	0.7319	0.6616	0.63	0.6319	0.6605	0.6856	0.7023	0.7292	0.7786	0.6906