Structural change in German chemical manufacturing industry during the 1990's. An analysis at the micro-level

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This version of September 3, 2006. *German chemical manufacturing industry is marked by two major structural changes during 1992–2004. Firstly, number of firms was ranging extensively: from 676 to 901, while only 96 firms represented balanced panel. Secondly, size of the firm dropped considerably—by 88%. This paper is intended to shed light on both phenomena. Based on reliable census data analysis suggests the former evidence be explained (i) by persistent poor performance of firms and (ii) by so called "general purpose technology" argument. The latter phenomenon was found to be a rational behaviour because numerous firms continually operated under decreasing returns to scale.* (*JEL*: D21, L23, L25, L65 *Keywords*: DEA, technical and scale efficiency, technological change, firm size, firm level data, chemical manufacturing).

I Introduction

The 1990's have brought about severe competitive challenges and new rules of playing game in chemical industry. Freeman 1999 claims that the last decade was accompanied by great changes, with the massive restructuring as the key feature:

> The days of the integrated chemical company were coming to an end, with companies abandoning noncore business segments in efforts to boost the creation of shareholder value. The reshaping of the industry had begun in the 1980's, but it was on a small scale compared to that in the 1990's.

Merges and acquisitions have performed a significant role in the adjustment process of the chemical industry (Weston et al. 1999). The German chemical industry have been doing tremendous job (Landau and Arora 1999) and continues to do so in development of the global and national economies in terms of employment, investments and value added as reported by the President of the Verband der Chemischen Industrie e.V. (Federation of the Chemical Industry, registered association).[1] Firstly, due to merges/de-merges, acquisition activities and entries/exits the

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[1] See `http://www.vci.de/default.asp?cmd=shd&docnr=116672&lastDokNr=116666` for details.

number of manufacturing firms representing chemical industry in Germany has been moving backwards and forwards greatly between 1992 and 2004. While the number of firms that were observed each year during the period under consideration is 96, the number of all firms has been ranging from 676 to 901 (see Tables 1 and 2). Secondly, during this period of time the average size (defined as the number of employees[2]) of the firm has decreased by about 88% (from 813 to 433). At the same time such average size has dropped only by approximately 31% (from 1998 to 1520) among 96 firms that were observed in all years, whereas among firms that were observed twelve or less times the average size has plummeted by about 110% (from 633 to 301). These figures also tell us that firms, which existed in all years from 1992 through 2004, were considerably larger than those, which operated less than 13 years. Such patterns suggest that relatively larger firms have better propensity to survive, and that economical/technological situation has put considerable pressure on smaller firms (see Swift 1999). Nevertheless, we note that even relatively larger firms have been persistently becoming smaller in size. Then the natural question arises: "Is the small beautiful?"

These phenomena beg for explanation and one intuitively comes up with an idea of scale economies. In addition to such hypothesis, the 'relative performance' argument comes into play. What if relatively smaller firm out-perform relatively smaller ones? In the literature the relationship between firm size and relative performance received thorough attention. On the one hand, larger firms have better penetration in the market and they can exploit economies of scale; moreover, larger firms have more funds to employ a better manager (Kumar 2003); studies which focus explicitly on the relationship between firm size and technical efficiency (*e.g.*, Alvarez and Crespi 2003, Gumbau-Albert and Maudos 2002, Meeusen and Broeck 1977, Torii 1992) found that the technical efficiency increases with the size of the firm. On the other hand, in the larger firm it is more difficult to keep all departments coordinated, that is, efficient (X-inefficiency, see Leibenstein 1966). Indeed, Table 1 shows that the mean of the output was remaining constant during time under consideration, while the kurtosis of the distribution was gradually increasing, implying that the producers of the largest output were producing even more. The different story is told by Table 2. While coefficient of variation, skewness and kurtosis remained virtually the same, the mean was rising considerably, suggesting a positive shift of the entire distribution, that is, all firms from balanced panel were producing more. On the other hand, we observe different patterns within inputs. Interestingly, within unbalanced panel (Table 1) the average expenditures for the labor compensation, capital usage and energy collapsed, while other categories remained virtually the same. Table 2 demonstrates us different reality.

During the period under consideration the difference between balanced and unbalanced samples is substantial. Among other distinctions, Table 3 reveals that while smallest firms (less than 49 employees) make up about quarter of the unbalanced panel, they constitute at most 4.2% of the balanced one. And vise versa, the largest firms (more than 1000 employees) represent approximately 10% of all firms in unbalanced sample, whereas balanced sample comprises up

[2]It is not uncommon to use number of employees as the proxy for firm size in the analysis of the chemical industry(*e.g.*, Grant II et al. 2002).

to 35% of the largest firms.

This paper is intended to shed light on two major structural changes in German chemical manufacturing industry during period 1992 through 2004 using modern frontier efficiency analysis. First, we plan to explain tremendous volatility in composition of industry; and second, to give reasons for aggregate tendency of firms to reduce its size. In this paper, we do a 'benchmark' analysis. The purpose of the estimates of the efficiency at the firm level is to measure the relative performance of the manufacturing units within an industry. We want to study the structural changes of the industry by looking at the distribution of the efficiencies and their changes over time. We also attempt to quantify potential scale economies. More specifically, we focus on the relationship between firm size and its performance by determining scale efficiency of the firm. The development of these indicators of the productive efficiency is bound to disclose the aggregate performance of the industry.

The paper unfolds as follows. Sections II provides an overview of methodology. Section III discusses data used in this study. Section IV presents the empirical results, and section V concludes.

II Methodology

This section provides an overview of methodology. The reader is referred to Färe 1988, Färe et al. 1994a, Färe and Primont 1995, and other cited references for more details.

An assessment of technical efficiency of firms requires the measurement of the best practice frontier and the identification of a point of reference for judging the relative efficiency level of the unit under inspection. In this paper, the best practice frontier is estimated as the upper boundary of the smallest convex free disposable cone of the observed data on inputs and outputs using the data envelopment analysis (DEA) estimator (DEA is initiated by Charnes et al. 1978; see Kneip et al. 1998 for a proof of consistency for the DEA estimator, as well as Kneip et al. 2003 for its limiting distribution). The reason for opting this non-parametric mathematical programming technique in favor of parametric statistical approaches is two-fold. Firstly, DEA does not impose an a priory assumption on technology underlying the the production process. Secondly, new developed bootstrap procedures enable to retrieve statistical properties of efficiency estimates, which furthers previously available point estimates to rigorous hypotheses testing (Simar and Wilson 1998, 2000; Simar and Zelenyuk 2003).

One of the a priori assumptions, which has to be made before employing DEA is the assumption about the returns to scale of the underlying technology. Literature suggests that different returns to scale assumptions may result in completely different conclusions (see discussion and empirical application in Färe et al. 1994b and Ray and Desli 1997). Fortunately, a reliable bootstrap procedure is developed, which puts forward a direct data driven test of the returns to scale (Simar and Wilson 2002). Authors suggest a technique not only to test for global returns to scale, but also test for the returns to scale at which a particular decision making unit is operating (known as a scale efficiency), and, if not scale efficient, the test for judgment at which portion of technology the unit is operating: increasing or decreasing returns to scale.

DEA allows two orientation choices, which reflect underlying technology. The first is output orientation, which fixes inputs on the observed level and boosts outputs as much as possible within best-practice technology. The second is input orientation, which, holding outputs constant, tries to decrease inputs within best-practice technology. In the analysis of manufacturing firms it is intuitive to assume output orientation, since resources are limited and not subject to very quick change, and economic purpose is to produce as much as possible.

A Technical efficiency

For each firm j ($j = 1, \ldots, K$) vector $x_j = (x_{j1}, \ldots, x_{jN}) \in \Re^N$ denotes N inputs, vector $y_j = (y_{j1}, \ldots, y_{jM}) \in \Re^M$ denotes M outputs. We assume that under technology T outputs are producible by inputs,

$$T = \{(x, y) : y \text{ are producible by } x\} \tag{1}$$

For output-based scores of technical efficiency the technology is represented by its production possibility set,

$$P(x) \equiv \{y : (x, y) \in T\} \tag{2}$$

The Shephard's (1970) output distance function is defined as

$$D^o(x, y) = \inf \left\{ \theta > 0 : \frac{y}{\theta} \in P(x) \right\} \tag{3}$$

This function by construction is positive and less or equal than unity, and is convenient in the sense of providing information about the amount of necessary increase of outputs to move a firm to a boundary or production possibility set.

Empirically, technical efficiencies are estimated via activity analysis models. For K observations, M outputs and N inputs an estimate of the Farrell output-oriented measure of technical efficiency can be calculated by solving a linear programming problem for each observation j ($j = 1, \ldots, K$):

$$\widehat{\mathrm{TE}}^o_j = \widehat{\theta}_j = \left[\widehat{D}^o_j(x, y|C)\right]^{-1} = \left[\max \left\{ \theta\colon \sum_{k=1}^{K} z_k y_{km} \geq y_j \theta, \sum_{k=1}^{K} z_k x_{kn} \leq x_j, z_k \geq 0 \right\}\right]^{-1} \tag{4}$$

for $m = 1, \ldots, M$ and $n = 1, \ldots, N$. Note that superscript o stands for output orientation, while C—for constant returns to scale (CRS). Other returns-to-scale are modeled by adjusting process operating levels z_k's; for variable returns to scale (VRS) we add a convexity constraint, an $\sum_{k=1}^{K} z_k = 1$ equality,[3] while for non-increasing returns to scale (NIRS) we add an $\sum_{k=1}^{K} z_k \leq 1$ inequality,[4] to linear programming problem in equation (4).

[3]This equality ensures that firm j is compared only to firms of similar size; such convexity restriction not utilized under CRS assumption, when firms of different sizes might be compared, that is, $\sum_{k=1}^{K} z_k$ might be greater/smaller than unity.

[4]This inequality ensures that firm j is not compared to other firms that are considerably larger, but maybe compared to smaller firms.

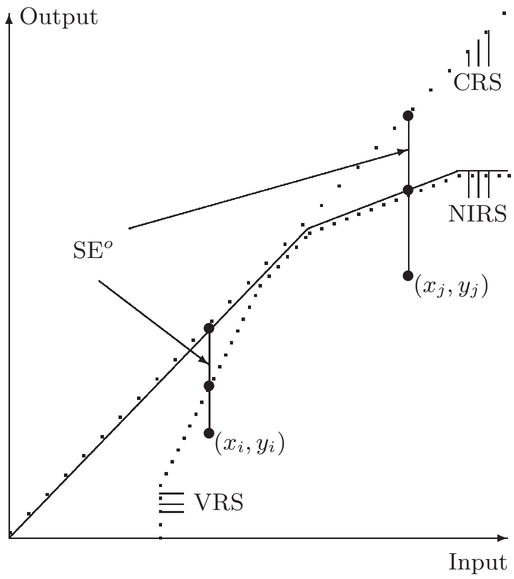

Fig. 1: Output-oriented Technical and Scale Efficiency

Figure 1 illustrates hypothetical one-input one-output production with three different technologies CRS, VRS and NIRS. Intuitively, in Figure 1 the vertical distance from an observation to CRS/VRS/NIRS best-practice frontier stands for output-oriented technical efficiency under CRS/VRS/NIRS assumption.

B Bias corrected technical efficiency

Although the DEA method is typically considered to be deterministic, the efficiency is still computed relatively to estimated and not true frontier. The efficiency scores obtained from a finite sample (in equation (4) from K observations) are subject to sampling variation of the estimated frontier (Simar and Wilson 1998). What is claimed is that estimated technical efficiency measures are too optimistic, due to the fact that the DEA estimate of the production set is necessarily a weak subset of the true production set under standard assumptions underlying DEA. It is proposed that the following bootstrap algorithm enables to retrieve bias-corrected estimates of original (as in equation (4)) "overstated" technical efficiencies:

(i). Obtain efficiency scores as in equation (4) for each firm j ($j = 1, \dots, K$).

(ii). Using a smooth bootstrap, generate a random sample of size K from $\widehat{\theta}_j$, $j = 1, \dots, K$; $\theta^*_{ib}, \dots, \theta^*_{Kb}$, where

$$\theta^*_j = \overline{\beta}^* + \frac{1}{\sqrt{1 + \frac{h^2}{\hat{\sigma}^2_\theta}}}(\widetilde{\theta}^*_j - \overline{\beta}^*) \tag{5}$$

$$\widetilde{\theta}^*_j = \begin{cases} \beta^* + h\epsilon^*_j & \text{if } \beta^* + h\epsilon^*_j \leq 1, \\ 2 - (\beta^* + h\epsilon^*_j) & \textit{otherwise} \end{cases} \tag{6}$$

$\beta^*_1, \dots, \beta^*_K$ is a bootstrap sample from original efficiency estimates as in step (i), h is the smoothing parameter of the kernel density estimate of original efficiency estimates, and ϵ_j^*, $j = 1, \ldots, K$ are random draws from the standard normal.

(iii). Compute y_{jb}^* for each j, $j = 1, \ldots, K$,

$$y_{jb}^* = \frac{\widehat{\theta}_j}{\theta_{jb}^*} y_j \tag{7}$$

(iv). Compute the bootstrap estimate $\widehat{\theta}_{jb}^*$ of $\widehat{\theta}_j$ for each j, $j = 1, \ldots, K$, by solving linear programming problems

$$\widehat{\theta}_{jb}^* = \left[\max \left\{ \theta \colon \sum_{k=1}^{K} z_k y_{km}^* \geq y_j \theta, \sum_{k=1}^{K} z_k x_{kn} \leq x_j, z_k \geq 0 \right\} \right]^{-1} \tag{8}$$

Repeat steps (ii) to (iv) B times to obtain estimates $\left[\widehat{\theta}_{jb}^*, b = 1, \ldots, B \right]$ for each j, $j = 1, \ldots, K$. Bias-corrected estimates of original technical efficiency from equation (4) are

$$\widetilde{\theta}_j = \widehat{\theta}_j - \widehat{bias}_j \tag{9}$$

$$\widehat{bias}_j = \frac{1}{B} \widehat{\theta}_{jb}^* - \widehat{\theta}_j \tag{10}$$

C Weighted technical efficiency

In our analysis we will also look at the performance of an average representative firm. As shown by Färe and Zelenyuk 2003 the simple averages of technical efficiency scores are misleading and weighted averages have to be adopted instead. For we do not have data on output prices, we rely on the price independent weights, which are the sum of each firm's share of each output normalized by the number of outputs M:

$$w_j = \frac{1}{M} \left(\frac{y_{j1}}{\sum\limits_{k=1}^{K} y_{k1}} + \frac{y_{j2}}{\sum\limits_{k=1}^{K} y_{k2}} + \ldots + \frac{y_{jM}}{\sum\limits_{k=1}^{K} y_{kM}} \right) = \frac{1}{M} \sum_{m=1}^{M} \frac{y_{jm}}{\sum\limits_{k=1}^{K} y_{km}} \tag{11}$$

for each j, $j = 1, \ldots, K$

D Non-parametric test of returns to scale

Simar and Wilson 2002 suggested a non-parametric test of returns to scale. Their idea of testing the null hypothesis that the technology is globally constant returns to scale versus the alternative hypothesis that the technology is globally variable returns to scale boils down to testing by how far is potential test statistic from its bootstrap analogue. The measure of scale efficiency[5], originally proposed by Färe and Grosskopf 1985,

$$s_j(x_j, y_j) = \frac{D_j^{CRS}(x_j, y_j)}{D_j^{VRS}(x_j, y_j)} \tag{12}$$

is used to facilitate the bootstrap test. Among others, the test statistic, which showed the best statistical properties is defined as

$$\widehat{S}_{2n}^{CRS} = \frac{\sum_{j=1}^{K} \widehat{D}_j^{CRS}(x_j, y_j)}{\sum_{j=1}^{K} \widehat{D}_j^{VRS}(x_j, y_j)} \tag{13}$$

If null hypothesis is true, then $\widehat{D}_j^{VRS}(x_j, y_j) = \widehat{D}_j^{CRS}(x_j, y_j)$ $j = 1, \ldots, K$, and $\widehat{s}_j = 1$. If alternative hypothesis is true, then $\widehat{s}_j \leq 1$. Since $\widehat{S}_{2n}^{CRS} \leq 1$, the null hypothesis is rejected if $\widehat{S}_{2n}^{CRS}$ is significantly less than unity.

Taking into account the importance of returns to scale assumption for DEA results, this data-driven test is advised to be performed before applying any DEA model. Additionally, this test can be easily translated to hypothesis testing by individuals. The CRS assumption is only feasible when all firms are operating at an optimal scale; *i.e.*, when scale elasticity is unity. However, for many reasons (*e.g.*, imperfect competition, financial constraints) it is more appropriate to assume variable returns to scale (see Coelli et al. 2002 for history and development of the this stream). Assuming CRS when VRS should be assumed in reality mixes up technical efficiency estimates exactly by scale efficiencies. Therefore, performing the individual returns-to-scale test is fairly important in case of scale efficiency analysis. The testing procedure is the following.

Under the null hypothesis that distance functions are equal under constant and variable returns to scale, $s_j(x_j, y_j) = 1$. Since by definition $s_j(x_j, y_j) \leq 1$, such null hypothesis is rejected if $s_j(x_j, y_j)$ is significantly less than unity; this test is performed for each j, $j = 1, \ldots, K$. For firm j, for which this null hypothesis is rejected, $s_j(x_j, y_j) \leq 1$ and this firm is scale inefficient. Then further test has to be performed. With another measure of scale inefficiency, defined as

$$\eta_j(x_j, y_j) = \frac{D_j^{NIRS}(x_j, y_j)}{D_j^{VRS}(x_j, y_j)} \tag{14}$$

and which is less or equal to unity by construction, the test concludes that firm is operating under increasing returns to scale (or in terms of Figure 1 it is a firm (x_i, y_i)) if $\eta_j(x_j, y_j)$ is significantly less than unity, and is operating under decreasing returns to scale (or in terms of Figure 1 it is a firm (x_j, y_j)) otherwise. All tests in this subsection are bootstrap tests, built on prior works by Simar and Wilson 1998, 2000, and we do not describe them in detail to conserve

[5]Scale efficiency measures how close is the manufacturing firm to potentially optimal scale. The measure of scale efficiency shows the expansion magnitude of output vector, from the observed firm to the optimal scale on the frontier function for output orientation.

space. Interested readers are referred to the original paper by Simar and Wilson 2002 for more details.

III Data

We use micro data from the German Cost Structure Census[6] of manufacturing for the period of 1992-2004 for the chemical industry.[7] The Cost Structure Census is gathered and compiled by the German Federal Statistical Office; firms are legally obliged to respond to the Cost Structure Census, so that missing observations due to non-response are precluded. The survey comprises all large German manufacturing firms which have 500 and more employees over the entire period, firms with 20-499 employees are included as a random sample that can be assumed as a representative for this size category as a whole. Since the year 2001 the statistic also contains firms with 1-19 employees. Due to merges/acquisitions and entries/exits the number of firms is different from year to year and varies considerably: 726, 695, 676, 857, 843, 848, 814, 835, 819, 794, 784, 901, and 881 for year 1992 through 2004, respectively; 96 firms represent balanced panel.[8] Unfortunately, Cost Structure Census does not allow to retrieve information on entry-exit or/and merging-demerging of firms for two reasons. First, every firm is assigned a unique 'id' and when firm with a certain 'id' disappears in the next year there are three possibilities for that: (i) firm actually exited the market, (ii) firm has been acquired by another firm, or (iii) firm changed the industry classification and is considered by statistical office as a new one. Second, appearing of a new firm or new 'id' might stem from three reasons: (i) it is really an entry, (ii) firm transferred from other industry, or (iii) that new merger occurred and statistical office assigns a new 'id'. The data-set does not differentiate these reasons.

Our measure of output is gross production. This mainly consists of the turnover and the net-change of the stock of the final products. We do not include turnover from activities that are classified as miscellaneous such as license fees, commissions, rents, leasing *etc.* because such

[6]Aggregate figures are published annually in Fachserie 4, Reihe 4.3 of Kostenstrukturerhebung im Verarbeitenden Gewerbe (diverse years).

[7]Industry "Manufacture of chemicals, chemical products and man-made fibres" (NACE.24 in accordance with the Classification of Economic Activities in the European Community) composed of the following sub-industries: Manufacture of basic chemicals (24.1), Manufacture of industrial gases (24.11), Manufacture of dyes and pigments (24.12), Manufacture of other inorganic basic chemicals (24.13), Manufacture of other organic basic chemicals (24.14), Manufacture of fertilizers and nitrogen compounds (24.15), Manufacture of plastics in primary forms (24.16), Manufacture of synthetic rubber in primary forms (24.17), Manufacture of pesticides and other agro-chemical products (24.2), Manufacture of paints, varnishes and similar coatings, printing ink and mastics (24.3), Manufacture of pharmaceuticals, medicinal chemicals and botanical products (24.4), Manufacture of basic pharmaceutical products (24.41), Manufacture of pharmaceutical preparations (24.42), Manufacture of soap and detergents, cleaning and polishing preparations, perfumes and toilet preparations (24.5), Manufacture of other chemical products (24.6), Manufacture of explosives (24.61), Manufacture of glues and gelatines (24.62), Manufacture of essential oils (24.63), Manufacture of photographic chemical material (24.64), Manufacture of prepared unrecorded media (24.65), Manufacture of other chemical products n.e.c. (24.66), Manufacture of man-made fibres (24.7).

[8]These numbers come from stratified sample (see Fritsch et al. 2004), but we have access to "population" number of all firms in the industry from 1995 to 2003, and confirm it is also quite volatile: 1255, 1236, 1222, 1226, 1258, 1245, 1253, 1315 and, 1332 respectively. As for the "population" data, only number of all firms can be retrieved, whereas in further analysis we have to rely on stratified sample, the best micro-data available for now.

revenue can not adequately be explained by the means of a production function.

Cost Structure Census contains information for a number of input categories.[9] These categories are payroll, employers' contribution to the social security system, fringe benefits, expenditure for material inputs, self-provided equipment and goods for resale, for energy, for external wage-work, external maintenance and repair, tax depreciation of fixed assets, subsidies, rents and leases, insurance costs, sales tax, other taxes and public fees, interest on outside capital as well as "other" costs such as license fees, bank charges and postage or expenses for marketing and transport.

Some of the cost categories including expenditure for external wage-work and for external maintenance and repair contain a relatively high share of reported zero values because many firms do not utilize these types of inputs. Such zeros make firms incomparable, and thus might bias DEA results. In order to reduce the number of reported zero input quantities, we aggregated the inputs into the following categories: (i) material inputs (intermediate material consumption plus commodity inputs), (ii) labor compensation (salaries and wages plus employer's social insurance contributions), (iii) energy consumption, (iv) user cost of capital (depreciation plus rents and leases), (v) external services (*e.g.*, repair costs and external wage-work), and (vi) "other" inputs related to production (*e.g.*, transportation services, consulting or marketing). For translating values into real terms, all input and output series were deflated using the producer price index for the respective industry.

IV Empirical results

This section first reports the technical efficiency results based on data envelopment analysis and then presents an analysis of scale efficiency of German chemical manufacturing firms. Findings from this section are intended to explain two structural changes in the chemical industry ensued during period 1992 through 2003.

A Technical efficiency

For each of thirteen years under consideration we performed a non-parametric tests of returns to scale (see section II, subsection D) to apply the appropriate DEA model to our data. In all thirteen cases the null hypothesis that the technology is constant returns to scale (Test 1) is overwhelmingly rejected. Further, we performed the Test 2, i.e., that the underlying technology is nonincreasing returns to scale. The *p-values* of the null hypothesis of Test 2 are 0.087, 0.052, 0.011, 0.179, 0.138, 0.032, 0.034, 0.078, 0.018, 0.209, 0.077, 0.061, and 0.007 for 1992 through 2004, respectively. Assuming the size of the test ten percent the technology is nonincreasing returns to scale in 1992, 1993, 1995, 1996, 1999, 2001, 2002, and 2003; in the rest years the technology is variable returns to scale.

With the knowledge of the appropriate technology we apply the homogeneous bootstrap

[9] Though the production theory framework requires real quantities, using expenditures as the proxies for inputs in production function is also practised in the literature (see *e.g.*, Paul et al. 2004, Paul and Nehring 2005).

following Simar and Wilson 1998 (see section II, subsection B). The year by year summary statistics of the technical efficiency for both unbalanced and balanced samples are presented in Table 4. The averages due to Färe and Zelenyuk 2003 of bias corrected technical efficiency scores by size categories are shown in Table 5.

The most striking result is the high level of technical inefficiency of German manufacturing firms—about 30%. This finding remains even if we look at firms within balanced sample, *i.e.*, firms that survived in all thirteen years under consideration. The lower panel of Table 4 does not contrast the upper one, implying that the distribution of technical efficiency in all years was virtually the same for balanced and unbalanced sample of firms. Moreover, neither clear decreasing, nor clear increasing trend in the values of efficiency is present. Thus, the "average" distance to the production possibility frontier did not increase during the period. This can indicate either unchanged technology and unchanged performance of the "average" firm, or changing of the performance in the same path as change of the underlying technology. Former is hardly convincing, since technological progress did positively influence the performance of the firm (*e.g.*, Brynjolfsson and Hitt 2000), and especially in chemical industry (see Swift 1999 and Weston et al. 1999). Thus, firms were going hand in hand with technological improvement, but were always legging behind the technological change. In the literature the latter evidence is known as a "general purpose technology" argument, which emphasizes that it takes time before newly implemented technology can be utilized 100 percent efficiently (see Helpman and Rangel 1999), and which explains continuous poor aggregate performance of the German chemical manufacturing firms.

The other observation worth mentioning is that while technical efficiency of an "average" German chemical manufacturing firm was fairly stable over the period under consideration; the mean was ranging only moderately from 0.70 to 0.75, remaining quite low. This implies that the same inputs in the different years could have produced 33–43 percent more of the observed output if the inputs were employed by firm with frontier production technology.

We have also looked at the rankings of the firms[10] between all years in terms of technical efficiency distribution. Thus we are able to investigate the changes in rankings of firms during the period under consideration. The Spearman's rank correlation coefficients between technical efficiency scores in different years are presented in Table 6. The correlation coefficients between one year lag is rather high as a rule, except for 1995/96 one, but lower than estimates of in the literature (*e.g.*, Førsund and Hjalmarsson 1979) indicating instability of the rankings. Further, the larger the lag between years the larger the discrepancy in the relative performance of the firm. This finding means quite low level of firmness in performance ranking between years, and together with "general purpose hypothesis" argument suggests an explanation for such big jumps in number of firms in different years; *i.e.*, the first major structural change in the aggregate performance of the chemical manufacturing industry during the 1990's.

Remarkably, a close look at the Table 5, which presents descriptive statistics of technical efficiency by size categories, reveals that in different years larger firms perform better or similar

[10]This is only possible for balanced sample, that is 96 firms.

than the average while smaller firms—worse. The firms with less than 49 employees are clearly lagging behind the firms from the rest size categories. The "average" firms from the rest five size categories are performing virtually similarly, with a little advantage of the largest size category.

The latter finding creates a puzzle, which bags for an explanation: larger firms are more technically efficient, which is desirable economically, so firms had better increased its size, while they did the opposite. Does this frustrate our "the small is beautiful" argument? The answer is "no". Resolving this puzzle is the subject of the following subsection.

B Scale efficiency

In the section IV, subcestion A we have already noticed that the industry has not been performing under global constant returns to scale, meaning that scale inefficiency is present. That is why, in current subsection we bother with analysis of scale efficiency of German chemical manufacturing firms. Instead of estimating scale efficiency in accordance with equation (12) (Färe and Grosskopf 1985), we rather employ Test 1 and Test 2 to individual firms (Simar and Wilson 2002).

We first consider firms, for which Test 1 is not rejected, that is scale efficient firms. The frequency of such firms in different years is presented in Table 7. The most remarkable finding is that the share of scale efficient has been constantly and persistently increasing from a little bit more than one thirds in 1992 to a half of all firms in 2004. If the power of the test is changed to five percent, the change of portion of scale efficient firms adjusts numerically: from 41 percent in 1992 to 57 percent in 2004. The argument, however, remains the same: during the period under inspection the number of scale efficient firms has been persistently growing in relative terms—in absolute terms this is not true because the total number of firms in the industry has been quite volatile in different years.

Additionally, we pay special attention to frequencies of scale efficient firms in different size categories. They are shown in Table 8 together with the number of firms in each size category. Three observations are worth noting. First, this table reveals that the fraction of scale efficient firms with less then 49 employees has been holding constant over the year. Second, the middle size firms ("50 to 249 employees") have experienced the largest growth in the share of scale efficient firms, over 100 percent: from 38 to 77 percent in size category "50 to 99 employees", and from 15 to 32 percent in size category "100 to 249 employees". Third, the share of scale efficient firms grew only moderately among larger firms. What follows from this table supports "the small is beautiful" argument even more. The finding that the share of larger firms as well as the size of the firm have been gradually decreasing over the years (see Table 3), plus the fact that the share of scale efficient firms has been increasing shad light on three above-mentioned observations.

In order to understand why increase of share of scale efficient firms goes together with the fact that the technical efficiency has been remaining virtually constant over the years we look at the remaining (scale inefficient) firms.

In order to analyze the nature of scale inefficiency, we perform the Test 2 (test null hypothesis: nonincreasing returns to scale versus alternative—variable returns to scale) on firms for which Test 1 was rejected, i.e., on scale inefficient firms. If the null hypothesis of Test 2 is rejected for a certain firm, it is scale inefficient due to increasing returns to scale, and has to exploit its scale and increase its size to be more scale efficient; if the null of the Test 2 is failed to be rejected then firm is operating on decreasing returns to scale portion of technology and has to decrease its size. Table 9 superimposes results from Table 7 and frequency of firms for which null hypothesis of Test 2 was not rejected, or scale inefficient firms due to decreasing returns to scale. The table shows that while the absolute number of scale efficient firms has been conceptually increasing, the number of scale inefficient firm is virtually constant with some jumps in 1996 and 1998.

The most remarkable finding, however, is that while a considerable portion of firms are scale inefficient the reason for that for majority of them is operating at the decreasing returns to scale portion of technology. According to Table 9, from 94 to 99 percent of scale inefficient firms in different years resemble firm i from Figure 1, and consequently had to reduce their size to be scale efficient—and this is exactly what they have been doing during the 1990's.

These findings suggest that for German chemical manufacturing firms improving technical efficiency has not been the first priority during the 1990's. Instead they have been paying special attention to establishment of an optimal scale, while technical efficiency has been supported on the same level. This tendency can be clearly read from Tables 7 and 4. And since scale inefficient firms cared about being scale efficient and simultaneously operated at the decreasing returns to scale, they have been reducing their size.

To sum up, scale efficiency turned out to be an important concept, and the estimates therein captured tendency of the aggregate performance of firms in the industry. The nature of scale inefficiency clearly renders an explanation for the second structural change in the industry, namely, the tendency of the firms to get smaller. The explanation of "the small is beautiful" phenomenon is robust over years.

V Concluding remarks

In this paper, the Farrell's measures of efficiency have been applied to German chemical manufacturing industry. We estimate and evaluate economic performance, focusing on technical and scale efficiency, during period 1992 through 2004. Proposed analysis is set to give reasons for two documented structural changes, (i) explosive nature of composition of industry; and (ii) aggregate tendency of firms to become smaller (so called "the small is beautiful" phenomenon).

Interestingly, the level of technical inefficiency is rather high—about 30%. This finding remains irrespective of sample considered. Moreover, the firms are persistently inefficient—during 1992 through 2004 the parameters of distribution were virtually the same in different years. In combination with the fact that firms' rankings in terms of technical efficiency were quite volatile during the period, the latter finding provides the rationale for the first structural change in the aggregate performance of the chemical manufacturing industry during the considered period.

The share of scale efficient firms has been gradually increasing during the period under consideration from 37 in 1992 to 51 percent in 2004. These are small firms that have been and are mostly scale efficient. Moreover, the middle size firms has been determining the growth of portion of scale efficient firms.

The most remarkable result, however, comes from analysis of nature of scale inefficiency. Among scale inefficient firms 94 to 99 percent of firms in different years are inefficient due to decreasing returns to scale; they had to reduce its size to become more scale efficient. These findings rationalize the fact that firms have been continuously becoming smaller during 1992 through 2004, that is, give reason for the second structural change in the industry.

Some policy implication can be drawn from these findings. While it is important to acknowledge the importance of becoming larger (for instance merging activities) for technical efficiency of a firm, it is also worth paying attention to the scale of the firm. More specifically, it is essential to analyze at which portion of technology firm is operating, and which implication does it have for decision about choosing the size of the firm. Our analysis proves that middle size firms (50 to 249 employees) are most successful if technical and scale efficiency performance are analyzed in combination.

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Table 1: Output and Inputs: Summary Statistics, 1992-2004, Unbalanced Sample

Year	N	Standard deviation	Coefficient of variation	Skewness	Kurtosis	Mean	Min	Median	Max
Output									
1992	726	1014054	4.8	11.9	163	211227	723.8	32292	15135792
1993	695	946245	4.7	11.5	152	201254	972.6	30628	13852398
1994	676	1020509	4.7	11.8	162	216919	938.7	34225	15884029
1995	857	960073	5.0	13.3	208	192545	1416.7	28973	17132570
1996	843	929676	4.8	13.5	217	194125	794.2	28873	16495555
1997	848	929299	4.6	14.7	259	201217	740.6	33325	18191370
1998	814	920986	4.5	14.7	256	205566	1340.0	36682	17037900
1999	835	890267	4.4	14.6	257	203617	1290.0	36467	16886770
2000	819	1018809	4.4	14.2	244	231730	1404.7	37957	18922732
2001	794	1005882	4.2	13.6	227	238612	1576.2	40720	18272336
2002	784	970146	4.3	14.1	238	227938	1922.3	42471	17911534
2003	901	880535	4.3	13.8	236	206873	1349.1	39053	16794964
2004	881	849574	3.9	13.1	241	218410	1903.4	40884	18135048
Material inputs									
1992	726	295399	3.9	9.2	102	76094	13.1	11916	3870093
1993	695	273051	3.9	9.2	101	69872	16.3	11297	3587467
1994	676	303941	3.9	9.4	106	77494	63.5	12133	3950658
1995	857	289164	4.0	10.4	133	72361	14.1	11518	4576338
1996	843	267036	3.7	10.0	126	71358	40.7	11540	4151797
1997	848	281611	3.6	10.7	152	77671	89.1	13061	4933885
1998	814	260934	3.3	10.6	151	78033	176.4	14800	4349543
1999	835	266184	3.4	10.6	157	79431	127.6	14610	4859704
2000	819	357248	3.7	11.8	191	96394	47.8	15913	6919231
2001	794	338598	3.5	11.3	177	97227	43.9	17676	6400430
2002	784	311322	3.4	11.0	171	92073	20.4	18628	5853762
2003	901	313071	3.7	12.1	192	83899	33.3	15940	5946344
2004	881	334876	3.7	11.8	190	89703	43.9	17206	6572756
Labor compensation									
1992	726	392343	5.6	13.0	189	69947	314.4	7639	6495467
1993	695	388277	5.6	12.7	180	69790	382.8	7730	6174036
1994	676	384160	5.4	12.5	175	70501	468.8	8201	6093890
1995	857	341333	5.9	14.4	232	58063	590.3	7064	6267881
1996	843	335416	5.7	14.2	228	59243	481.6	7338	6146896
1997	848	299487	5.4	15.8	289	55749	368.0	7753	5901589
1998	814	296152	5.2	15.2	269	57409	420.8	8762	5489492
1999	835	289585	5.0	15.0	263	57850	454.8	9692	5319419
2000	819	290629	5.0	15.0	262	58331	433.2	9955	5343963
2001	794	287970	4.8	14.0	233	60383	437.9	10843	5062888
2002	784	281063	4.9	14.6	248	57650	431.8	11567	5226464
2003	901	268607	4.9	14.9	273	54424	567.2	9648	5680023
2004	881	243885	4.5	16.0	342	54171	864.6	9389	5723708
Energy consumption									
1992	726	73707	7.3	15.5	278	10032	2.7	462	1512668
1993	695	70387	7.5	15.3	269	9439	2.5	455	1416196
1994	676	67928	7.3	15.6	284	9361	6.0	477	1391076
1995	857	60770	7.6	16.7	323	7973	4.5	447	1341809
1996	843	62842	7.7	17.9	376	8146	8.3	451	1467619
1997	848	64657	7.9	20.7	496	8154	2.0	441	1638512
1998	814	58748	7.2	19.1	427	8190	8.7	498	1412024
1999	835	33986	4.9	11.5	168	6931	1.5	528	587401
2000	819	38822	5.1	11.5	167	7616	9.8	539	666958
2001	794	46045	5.3	12.6	196	8660	11.9	601	829509
2002	784	44988	5.3	12.3	186	8539	13.3	611	753911

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Table 1 – Continued

Year	N	Standard deviation	Coefficient of variation	Skewness	Kurtosis	Mean	Min	Median	Max
2003	901	44217	5.8	15.6	296	7633	3.9	507	953492
2004	881	40033	5.2	13.0	219	7765	6.8	545	806895
Capital									
1992	726	94515	5.3	11.9	161	17745	40.4	1803	1363207
1993	695	95674	5.3	11.6	153	18046	36.6	1986	1345946
1994	676	94270	5.1	11.4	148	18567	34.8	2053	1312000
1995	857	80973	5.4	12.8	187	14906	46.1	1795	1270690
1996	843	79316	5.2	12.5	181	15186	34.0	1753	1264177
1997	848	68061	4.9	13.7	229	13985	59.5	1787	1272745
1998	814	67932	4.7	13.9	236	14342	54.4	1972	1278483
1999	835	68063	4.6	13.7	231	14831	54.3	2127	1281434
2000	819	69828	4.6	13.4	222	15226	51.7	2213	1301647
2001	794	70774	4.5	13.1	211	15620	46.3	2417	1290556
2002	784	71060	4.7	13.5	222	15230	38.7	2532	1319370
2003	901	68208	4.8	14.0	242	14202	73.7	2287	1345081
2004	881	54751	4.0	12.0	201	13617	57.0	2314	1106204
External services									
1992	726	78228	6.2	12.4	183	12663	3.0	747	1393239
1993	695	70937	6.1	12.4	184	11597	5.3	729	1276040
1994	676	77942	6.5	13.6	215	12076	5.3	819	1440158
1995	857	77324	7.3	16.3	304	10650	9.4	714	1627759
1996	843	93382	7.4	15.6	276	12579	3.4	740	1845954
1997	848	96622	7.5	17.2	329	12927	5.3	796	2021390
1998	814	95345	7.3	18.0	361	13106	3.5	878	2094028
1999	835	87430	6.7	17.2	340	13052	5.9	1082	1916457
2000	819	100066	7.0	17.1	321	14385	14.8	1143	1983162
2001	794	118516	7.6	17.8	350	15634	13.2	1182	2557606
2002	784	99778	7.2	17.0	320	13833	8.0	1257	2080831
2003	901	75399	6.0	15.1	271	12506	2.7	1017	1553493
2004	881	66145	5.6	16.7	357	11818	7.6	1032	1560612
"Other" inputs related to production									
1992	726	171957	4.5	11.0	144	37904	20.2	4348	2708440
1993	695	171378	4.4	10.1	122	38917	88.9	4201	2458878
1994	676	194747	4.6	11.5	161	42281	64.3	4553	3317415
1995	857	170214	4.7	11.6	160	35912	68.4	3883	2913760
1996	843	181311	4.7	11.8	168	38437	40.0	3770	3161921
1997	848	172263	4.5	13.3	229	38268	24.6	4213	3463636
1998	814	182971	4.5	13.1	228	40584	40.5	4615	3726024
1999	835	246071	5.6	17.4	374	44078	39.7	4679	5776583
2000	819	226675	5.0	13.3	220	45376	26.1	5062	4365538
2001	794	267802	5.5	15.5	292	48938	32.8	5256	5714944
2002	784	272755	5.9	16.9	331	45940	118.9	5642	5938789
2003	901	224918	5.4	13.6	217	41305	112.6	4938	4041141
2004	881	228556	5.1	12.4	197	45081	152.6	5162	4437297

Notes: output and all inputs are in real terms, thousands of Euros;

Table 2: Output and Inputs: Summary Statistics, 1992-2004, Balanced Sample

Year	N	Standard deviation	Coefficient of variation	Skewness	Kurtosis	Mean	Min	Median	Max
Output									
1992	96	1648205	3.0	7.5	65.7	542488	6243.3	192286	15135792
1993	96	1515083	3.0	7.4	64.4	510878	7847.5	170329	13852398
1994	96	1705189	3.1	7.8	69.9	543095	9687.3	188532	15884029
1995	96	1830029	3.2	7.9	71.4	577110	11942.1	194235	17132570
1996	96	1765289	3.1	7.9	70.6	571730	13036.4	203263	16495555
1997	96	1941885	3.1	7.9	71.5	619926	13877.6	205214	18191370
1998	96	1834287	3.0	7.7	68.8	607411	10771.3	209307	17037900
1999	96	1824004	3.0	7.7	68.0	603099	10845.9	209939	16886770
2000	96	2040054	3.0	7.7	68.5	670652	12221.1	225319	18922732
2001	96	1989084	3.0	7.6	65.8	663876	11902.6	241900	18272336
2002	96	1961059	2.9	7.4	64.1	669799	11216.1	218074	17911534
2003	96	1871315	2.8	7.1	59.3	666652	9085.9	204895	16794964
2004	96	1992103	2.9	7.4	63.2	678018	12903.2	191254	18135048
Material inputs									
1992	96	451534	2.4	5.8	42.7	187446	356.4	68917	3734859
1993	96	395101	2.3	5.5	38.6	171435	111.6	63378	3186899
1994	96	468853	2.5	6.1	46.0	188843	199.8	65829	3950658
1995	96	524808	2.5	6.5	52.3	207421	287.4	75017	4576338
1996	96	480456	2.4	6.3	49.9	201432	454.9	73139	4151797
1997	96	566246	2.5	6.5	52.0	228293	518.7	84181	4933885
1998	96	514977	2.3	6.1	45.9	222203	682.7	86626	4349543
1999	96	545895	2.5	6.8	56.2	222618	402.3	88947	4859704
2000	96	746465	2.8	7.7	67.5	266760	651.2	108098	6919231
2001	96	703000	2.7	7.3	62.7	259191	651.2	109301	6400430
2002	96	658656	2.6	6.9	56.6	257409	890.4	96355	5853762
2003	96	666416	2.5	6.9	57.3	262603	962.0	95659	5946344
2004	96	729339	2.7	7.1	60.1	269656	934.3	106906	6572756
Labor compensation									
1992	96	558766	3.1	7.3	62.4	178929	2081.2	52951	5060447
1993	96	548361	3.1	7.4	64.5	174500	2357.9	52336	5007826
1994	96	541043	3.1	7.5	65.0	172157	2760.0	55118	4948980
1995	96	576142	3.2	7.6	67.1	179186	2112.2	52466	5309250
1996	96	567776	3.2	7.5	65.1	179817	2025.0	55610	5196795
1997	96	582507	3.2	7.6	66.7	180787	2443.8	55051	5359060
1998	96	592834	3.2	7.3	62.7	187348	2769.6	59049	5372067
1999	96	592580	3.1	7.1	59.5	191245	2688.1	59401	5299292
2000	96	589777	3.1	7.3	62.4	191833	2712.5	61183	5343963
2001	96	577299	3.0	6.7	54.5	191659	2776.3	62020	5050351
2002	96	592787	3.0	6.9	56.1	195300	3129.7	59479	5226464
2003	96	641724	3.1	6.9	57.2	206226	3200.8	59290	5680023
2004	96	645025	3.1	7.0	57.7	207286	2898.1	57700	5723708
Energy consumption									
1992	96	155385	5.3	9.2	88.3	29338	24.5	2713	1512668
1993	96	145623	5.2	9.2	87.8	28121	42.2	3040	1416196
1994	96	143145	5.1	9.2	87.5	27819	40.5	3012	1391076
1995	96	138145	5.1	9.1	87.3	26986	59.0	2698	1341809
1996	96	150505	5.5	9.3	89.2	27598	55.1	2698	1467619
1997	96	168008	5.6	9.3	89.4	30031	63.4	2935	1638512
1998	96	145143	5.3	9.2	88.2	27211	104.4	3028	1412024
1999	96	59449	3.3	6.5	49.9	18195	79.0	2581	504957
2000	96	75695	3.5	7.0	57.5	21569	63.2	2897	666958
2001	96	91371	3.7	7.5	64.7	24731	88.0	3245	829509
2002	96	83968	3.6	7.3	61.9	23405	89.3	3080	753911

Continued on Next Page...

Table 2 – Continued

Year	N	Standard deviation	Coefficient of variation	Skewness	Kurtosis	Mean	Min	Median	Max
2003	96	76217	3.5	7.3	61.0	21996	90.4	3894	681030
2004	96	90392	3.8	7.4	61.9	23901	74.3	3963	806895
Capital									
1992	96	141641	3.2	7.5	65.5	44265	436.4	11464	1297707
1993	96	139986	3.1	7.4	64.5	44925	689.2	11222	1278969
1994	96	136386	3.0	7.3	63.0	44917	666.0	11466	1240244
1995	96	130128	2.9	7.1	60.5	44524	727.9	11387	1173400
1996	96	125446	2.9	7.0	59.5	43861	712.2	12607	1127247
1997	96	125738	2.9	7.0	59.6	44110	676.8	11817	1130353
1998	96	124282	2.8	7.0	59.1	44144	625.7	12024	1115705
1999	96	125523	2.8	6.9	57.9	44726	600.2	12309	1121363
2000	96	126246	2.8	6.8	56.6	45338	567.6	12253	1121368
2001	96	126225	2.8	6.7	56.0	45427	540.9	12138	1118141
2002	96	126151	2.8	6.7	55.3	45599	516.5	12100	1114288
2003	96	126988	2.8	6.7	54.7	45938	499.7	11969	1118472
2004	96	125933	2.7	6.6	54.1	45861	492.9	11862	1106204
External services									
1992	96	146728	4.4	8.5	78.7	33301	43.8	5631	1393239
1993	96	135720	4.4	8.3	75.8	30846	27.7	4578	1276040
1994	96	150967	4.7	8.7	80.7	32118	94.0	5440	1440158
1995	96	170270	4.8	8.7	81.5	35834	125.8	5693	1627759
1996	96	191389	5.0	9.0	84.8	38070	117.9	5324	1845954
1997	96	208845	5.1	9.1	86.1	40554	145.1	5777	2021390
1998	96	215613	5.2	9.1	87.4	41172	100.5	6064	2094028
1999	96	200138	4.7	8.7	81.8	42597	233.9	6208	1916457
2000	96	195913	4.4	8.3	75.9	44876	234.7	6545	1843938
2001	96	268370	5.0	8.7	80.8	53637	107.4	5858	2557606
2002	96	223341	4.6	8.2	73.5	48913	223.8	6449	2080831
2003	96	176262	4.0	7.3	59.5	44416	191.0	7359	1553493
2004	96	171109	4.1	7.8	67.2	41481	108.4	7267	1560612
"Other" inputs related to production									
1992	96	242795	2.6	5.7	40.1	92349	606.6	23230	1959246
1993	96	237277	2.6	5.3	35.1	91901	519.8	22423	1842322
1994	96	259344	2.7	6.0	44.7	94373	319.4	23578	2149557
1995	96	244833	2.6	5.5	38.5	94798	922.2	23572	1950391
1996	96	262044	2.7	5.9	44.1	98526	833.4	26219	2180717
1997	96	291597	2.7	5.7	40.5	109526	767.6	31563	2363282
1998	96	280493	2.5	4.8	29.1	111543	830.2	34201	2048849
1999	96	339209	2.8	5.8	42.8	120995	786.8	33837	2795091
2000	96	395004	2.9	6.2	46.8	134667	865.6	37619	3326033
2001	96	413488	3.0	6.3	47.9	135644	1125.4	40291	3492273
2002	96	450661	3.3	6.7	52.7	137544	1024.2	34482	3890194
2003	96	464974	3.3	6.7	53.9	141353	995.9	32024	4041141
2004	96	498752	3.4	7.1	58.9	148725	626.4	37088	4437297

Notes: output and all inputs are in real terms, thousands of Euros

Table 3: Frequency of Firms, 1992 through 2004,
Unbalanced and Balanced Samples

Size category	Number of Firms	Share of all Firms, %	Cumulated Share of all Firms, %	Number of Firms	Share of all Firms, %	Cumulated Share of all Firms, %
	un-balanced sample			balanced sample		
1992						
less than 49 employees	191	26.31	26.31	4	4.17	4.17
50-99 employees	133	18.32	44.63	10	10.42	14.58
100-249 employees	151	20.80	65.43	16	16.67	31.25
250-499 employees	93	12.81	78.24	12	12.50	43.75
500-999 employees	65	8.95	87.19	19	19.79	63.54
more than 1000 emp.	93	12.81	100.00	35	36.46	100.00
total	726	100.00		96	100.00	
1993						
less than 49 employees	176	25.32	25.32	3	3.13	3.13
50-99 employees	143	20.58	45.90	11	11.46	14.58
100-249 employees	146	21.01	66.91	19	19.79	34.38
250-499 employees	85	12.23	79.14	11	11.46	45.83
500-999 employees	63	9.06	88.20	19	19.79	65.63
more than 1000 emp.	82	11.80	100.00	33	34.38	100.00
total	695	100.00		96	100.00	
1994						
less than 49 employees	168	24.85	24.85	3	3.13	3.13
50-99 employees	143	21.15	46.01	13	13.54	16.67
100-249 employees	136	20.12	66.12	16	16.67	33.33
250-499 employees	88	13.02	79.14	11	11.46	44.79
500-999 employees	62	9.17	88.31	21	21.88	66.67
more than 1000 emp.	79	11.69	100.00	32	33.33	100.00
total	676	100.00		96	100.00	
1995						
less than 49 employees	251	29.29	29.29	3	3.13	3.13
50-99 employees	176	20.54	49.82	9	9.38	12.50
100-249 employees	186	21.70	71.53	20	20.83	33.33
250-499 employees	96	11.20	82.73	12	12.50	45.83
500-999 employees	71	8.28	91.02	22	22.92	68.75
more than 1000 emp.	77	8.98	100.00	30	31.25	100.00
total	857	100.00		96	100.00	
1996						
less than 49 employees	242	28.71	28.71	3	3.13	3.13
50-99 employees	178	21.12	49.82	10	10.42	13.54
100-249 employees	184	21.83	71.65	19	19.79	33.33
250-499 employees	91	10.79	82.44	11	11.46	44.79
500-999 employees	67	7.95	90.39	22	22.92	67.71
more than 1000 emp.	81	9.61	100.00	31	32.29	100.00
total	843	100.00		96	100.00	
1997						
less than 49 employees	248	29.25	29.25	2	2.08	2.08
50-99 employees	165	19.46	48.70	10	10.42	12.50
100-249 employees	191	22.52	71.23	21	21.88	34.38
250-499 employees	86	10.14	81.37	11	11.46	45.83
500-999 employees	73	8.61	89.98	17	17.71	63.54
more than 1000 emp.	85	10.02	100.00	35	36.46	100.00
total	848	100.00		96	100.00	
1998						
less than 49 employees	218	26.78	26.78	2	2.08	2.08
50-99 employees	169	20.76	47.54	12	12.50	14.58
100-249 employees	182	22.36	69.90	19	19.79	34.38
250-499 employees	91	11.18	81.08	13	13.54	47.92

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Table 3 – Continued

Size category	Number of Firms	Share of all Firms, %	Cumulated Share of all Firms, %	Number of Firms	Share of all Firms, %	Cumulated Share of all Firms, %
	un-balanced sample			balanced sample		
500-999 employees	77	9.46	90.54	19	19.79	67.71
more than 1000 emp.	77	9.46	100.00	31	32.29	100.00
total	814	100.00		96	100.00	
1999						
less than 49 employees	189	22.63	22.63	1	1.04	1.04
50-99 employees	188	22.51	45.15	14	14.58	15.63
100-249 employees	197	23.59	68.74	16	16.67	32.29
250-499 employees	103	12.34	81.08	16	16.67	48.96
500-999 employees	79	9.46	90.54	17	17.71	66.67
more than 1000 emp.	79	9.46	100.00	32	33.33	100.00
total	835	100.00		96	100.00	
2000						
less than 49 employees	180	21.98	21.98	1	1.04	1.04
50-99 employees	185	22.59	44.57	13	13.54	14.58
100-249 employees	198	24.18	68.74	16	16.67	31.25
250-499 employees	106	12.94	81.68	15	15.63	46.88
500-999 employees	74	9.04	90.72	18	18.75	65.63
more than 1000 emp.	76	9.28	100.00	33	34.38	100.00
total	819	100.00		96	100.00	
2001						
less than 49 employees	162	20.40	20.40	2	2.08	2.08
50-99 employees	186	23.43	43.83	12	12.50	14.58
100-249 employees	194	24.43	68.26	20	20.83	35.42
250-499 employees	103	12.97	81.23	11	11.46	46.88
500-999 employees	76	9.57	90.81	20	20.83	67.71
more than 1000 emp.	73	9.19	100.00	31	32.29	100.00
total	794	100.00		96	100.00	
2002						
less than 49 employees	151	19.26	19.26	1	1.04	1.04
50-99 employees	180	22.96	42.22	13	13.54	14.58
100-249 employees	201	25.64	67.86	16	16.67	31.25
250-499 employees	108	13.78	81.63	16	16.67	47.92
500-999 employees	74	9.44	91.07	19	19.79	67.71
more than 1000 emp.	70	8.93	100.00	31	32.29	100.00
total	784	100.00		96	100.00	
2003						
less than 49 employees	207	22.97	22.97	1	1.04	1.04
50-99 employees	223	24.75	47.72	14	14.58	15.63
100-249 employees	211	23.42	71.14	16	16.67	32.29
250-499 employees	114	12.65	83.80	15	15.63	47.92
500-999 employees	77	8.55	92.34	21	21.88	69.79
more than 1000 emp.	69	7.66	100.00	29	30.21	100.00
total	901	100.00		96	100.00	
2004						
less than 49 employees	194	22.02	22.02	2	2.08	2.08
50-99 employees	218	24.74	46.77	13	13.54	15.63
100-249 employees	217	24.63	71.40	17	17.71	33.33
250-499 employees	112	12.71	84.11	16	16.67	50.00
500-999 employees	76	8.63	92.74	22	22.92	72.92
more than 1000 emp.	64	7.26	100.00	26	27.08	100.00
total	881	100.00		96	100.00	

Table 4: Technical Efficiency: Summary Statistics, 1992-2004, Unbalanced and Balanced Samples.[4a]

Year	N	Mean[4b]	St.d.	Coef. of Var.	Skewness	Kurtosis	min	Q25	Median	Q75
					Unbalanced sample					
1992	726	0.74	0.13	0.19	-0.53	2.97	0.24	0.60	0.69	0.78
1993	695	0.73	0.12	0.19	-0.45	3.04	0.21	0.59	0.67	0.76
1994	676	0.74	0.11	0.16	-0.37	2.78	0.34	0.61	0.69	0.77
1995	857	0.75	0.13	0.18	-0.52	2.90	0.24	0.61	0.70	0.78
1996	843	0.74	0.12	0.17	-0.56	3.24	0.28	0.62	0.69	0.77
1997	848	0.74	0.12	0.18	-0.59	3.14	0.22	0.62	0.70	0.78
1998	814	0.75	0.12	0.17	-0.43	2.83	0.29	0.62	0.70	0.79
1999	835	0.72	0.13	0.19	-0.42	2.89	0.24	0.58	0.67	0.77
2000	819	0.77	0.12	0.17	-0.72	3.48	0.27	0.63	0.72	0.80
2001	794	0.74	0.12	0.17	-0.64	3.21	0.28	0.63	0.72	0.79
2002	784	0.74	0.12	0.16	-0.65	3.65	0.25	0.63	0.71	0.78
2003	901	0.71	0.12	0.18	-0.27	2.71	0.28	0.57	0.66	0.75
2004	881	0.70	0.13	0.20	-0.31	2.69	0.24	0.56	0.65	0.74
					Balanced sample					
1992	96	0.75	0.11	0.15	-1.00	4.94	0.28	0.66	0.74	0.81
1993	96	0.74	0.10	0.14	-0.39	2.58	0.40	0.64	0.73	0.79
1994	96	0.75	0.09	0.13	-0.41	2.28	0.48	0.67	0.76	0.82
1995	96	0.75	0.09	0.13	-0.57	2.74	0.50	0.67	0.76	0.81
1996	96	0.75	0.10	0.13	-0.70	3.41	0.40	0.67	0.75	0.80
1997	96	0.74	0.10	0.13	-1.00	3.93	0.41	0.68	0.75	0.80
1998	96	0.74	0.10	0.14	-0.57	2.67	0.50	0.68	0.75	0.82
1999	96	0.71	0.12	0.16	-0.69	2.88	0.36	0.62	0.75	0.80
2000	96	0.77	0.10	0.14	-1.10	4.03	0.39	0.71	0.78	0.84
2001	96	0.74	0.11	0.15	-1.07	4.32	0.34	0.69	0.76	0.82
2002	96	0.74	0.11	0.15	-1.08	5.31	0.31	0.68	0.73	0.78
2003	96	0.70	0.11	0.15	-0.60	3.84	0.31	0.63	0.70	0.78
2004	96	0.69	0.12	0.18	-0.53	2.68	0.36	0.59	0.67	0.75

[4a] Technical Efficiency are bias corrected efficiency scores following Simar and Wilson 1998.
[4b] Averages are due to Färe and Zelenyuk 2003.

Table 5: Averages[5a] of Technical Efficiency and Number of Firms by Size Categories, 1992-2004.

	1992		**1993**		**1994**		**1995**		**1996**		**1997**		**1998**	
Size Category	N	mean	N	mean	N	mean	N	mean	N	mean	N	mean	N	mean
less than 49 employees	191	0.66	176	0.65	168	0.66	251	0.67	242	0.67	248	0.70	218	0.71
50-99 employees	133	0.71	143	0.69	143	0.71	176	0.68	178	0.68	165	0.68	169	0.69
100-249 employees	151	0.73	146	0.71	136	0.72	186	0.73	184	0.72	191	0.70	182	0.70
250-499 employees	93	0.72	85	0.70	88	0.74	96	0.74	91	0.73	86	0.74	91	0.73
500-999 employees	65	0.73	63	0.71	62	0.73	71	0.76	67	0.76	73	0.77	77	0.76
more than 1000 emp.	93	0.74	82	0.74	79	0.75	77	0.75	81	0.75	85	0.74	77	0.75
total	726	0.74	695	0.73	676	0.74	857	0.75	843	0.74	848	0.74	814	0.75

	1999		**2000**		**2001**		**2002**		**2003**		**2004**	
Size Category	N	mean	N	mean	N	mean	N	mean	N	mean	N	mean
less than 49 employees	189	0.66	180	0.71	162	0.70	151	0.69	207	0.67	194	0.67
50-99 employees	188	0.65	185	0.71	186	0.70	180	0.71	223	0.66	218	0.63
100-249 employees	197	0.69	198	0.73	194	0.74	201	0.72	211	0.69	217	0.69
250-499 employees	103	0.72	106	0.76	103	0.76	108	0.74	114	0.71	112	0.69
500-999 employees	79	0.75	74	0.77	76	0.75	74	0.74	77	0.72	76	0.72
more than 1000 emp.	79	0.72	76	0.77	73	0.74	70	0.74	69	0.71	64	0.70
total	835	0.72	819	0.77	794	0.74	784	0.74	901	0.71	881	0.70

[5a] Averages are due to Färe and Zelenyuk 2003.

Table 6: The Spearman's Rank Correlation Coefficients of bias corrected technical efficiency scores between Different Years.[6a]

	..1992	..1993	..1994	..1995	..1996	..1997	..1998	..1999	..2000	..2001	..2002	..2003	..2004
TE_{1992}	1.00												
TE_{1993}	*0.81*	1.00											
TE_{1994}	0.69	*0.76*	1.00										
TE_{1995}	*0.54*	0.62	*0.69*	1.00									
TE_{1996}	0.48	*0.52*	0.53	*0.64*	1.00								
TE_{1997}	*0.28*	0.30	*0.29*	0.46	*0.67*	1.00							
TE_{1998}	0.28	*0.23*	0.28	*0.41*	0.41	*0.68*	1.00						
TE_{1999}	*0.34*	0.24	*0.31*	0.38	*0.45*	0.58	*0.67*	1.00					
TE_{2000}	0.32	*0.26*	0.35	*0.39*	0.36	*0.42*	0.50	*0.60*	1.00				
TE_{2001}	*0.35*	0.32	*0.39*	0.42	*0.41*	0.53	*0.48*	0.54	*0.74*	1.00			
TE_{2002}	0.31	*0.24*	0.32	*0.32*	0.42	*0.44*	0.41	*0.54*	0.53	*0.60*	1.00		
TE_{2003}	*0.31*	0.27	*0.43*	0.34	*0.35*	0.45	*0.53*	0.50	*0.63*	0.70	*0.68*	1.00	
TE_{2004}	0.27	*0.22*	0.35	*0.26*	0.31	*0.43*	0.47	*0.44*	0.54	*0.61*	0.60	*0.78*	1.00

[6a] All correlation coefficients are significant at 1% level.

Table 7: Frequency of Scale Efficient Firms (for which Test 1 is not rejected).[7a]

year	Total N	N of SE Firms[7b]	N of SE Firms, %
1992	726	271	0.37
1993	695	258	0.37
1994	676	225	0.33
1995	857	357	0.42
1996	843	310	0.37
1997	848	410	0.48
1998	814	465	0.57
1999	835	445	0.53
2000	819	369	0.45
2001	794	389	0.49
2002	784	365	0.47
2003	901	474	0.53
2004	881	449	0.51

[7a] The size of the test is 10 per cent.
[7b] 'SE' stands for scale efficient.

Table 8: Frequency of Scale Efficient Firms by Size Categories, 1992-2004.

	1992		1993		1994		1995		1996		1997		1998	
Size Category	N	freq.[8a]	N	freq.	N	freq.	N	freq.	N	freq.	N	freq.	N	freq.
less than 49 employees	191	0.88	176	0.89	168	0.82	251	0.82	242	0.83	248	0.81	218	0.88
50-99 employees	133	0.38	143	0.36	143	0.26	176	0.45	178	0.31	165	0.64	169	0.78
100-249 employees	151	0.15	146	0.15	136	0.11	186	0.19	184	0.13	191	0.32	182	0.54
250-499 employees	93	0.16	85	0.16	88	0.17	96	0.20	91	0.16	86	0.27	91	0.27
500-999 employees	65	0.08	63	0.10	62	0.11	71	0.10	67	0.15	73	0.14	77	0.10
more than 1000 emp.	93	0.12	82	0.10	79	0.16	77	0.13	81	0.09	85	0.09	77	0.12
total	726	0.37	695	0.37	676	0.33	857	0.42	843	0.37	848	0.48	814	0.57

	1999		2000		2001		2002		2003		2004	
Size Category	N	freq.	N	freq.	N	freq.	N	freq.	N	freq.	N	freq.
less than 49 employees	189	0.95	180	0.89	162	0.96	151	0.95	207	0.98	194	0.85
50-99 employees	188	0.84	185	0.56	186	0.59	180	0.64	223	0.70	218	0.77
100-249 employees	197	0.43	198	0.29	194	0.28	201	0.27	211	0.31	217	0.32
250-499 employees	103	0.16	106	0.21	103	0.32	108	0.19	114	0.24	112	0.21
500-999 employees	79	0.08	74	0.19	76	0.24	74	0.19	77	0.16	76	0.13
more than 1000 emp.	79	0.04	76	0.17	73	0.25	70	0.24	69	0.14	64	0.22
total	835	0.53	819	0.45	794	0.49	784	0.47	901	0.53	881	0.51

[8a] 'freq' stands for frequency in per cent.

Table 9: Frequency of scale efficient (Test 1 is not rejected) and scale inefficient firms with inefficiency due to Decreasing Returns to Scale (Test 2 is not rejected), 1992–2004.[9a]

	scale efficient			scale inefficient		
year	Total N	N of SE	N of SE, %	N of SI	Due to DRS	Due to DRS, %[9a]
1992	726	271	0.37	455	452	0.99
1993	695	258	0.37	437	432	0.99
1994	676	225	0.33	451	449	0.99
1995	857	357	0.42	500	495	0.99
1996	843	310	0.37	533	531	0.99
1997	848	410	0.48	438	432	0.99
1998	814	465	0.57	349	319	0.91
1999	835	445	0.53	390	379	0.97
2000	819	369	0.45	450	437	0.97
2001	794	389	0.49	405	402	0.99
2002	784	365	0.47	419	416	0.99
2003	901	474	0.53	427	424	0.99
2004	881	449	0.51	432	404	0.94

[9a] The size of the test is 10 per cent; this frequency increases even more when size of the test is increased.
[9b] 'SE' stands for scale efficient; 'SI' stands for scale inefficient; 'DRS' stands for decreasing returns to scale.