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Why Small is Beautiful?

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Downsizing in German chemical manufacturing industry during the 1990s. Why small is beautiful?[§]

Oleg Badunenko[*]

August, 2007

Abstract

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.

Keywords: DEA, technical and scale efficiency, technological change, firm size, firm level data, chemical manufacturing

JEL classification: D21, L23, L25, L65

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1 Introduction

The 1990s 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 1980s, but it was on a small scale compared to that in the 1990s.

In addition to changed rules Bathelt (1995) discusses substantial reorganization and modernization activities happening in the German chemical industry as a result of willingness to overcome the crisis of Fordism (various rigidities in the industrial sector). The chemical industry is the third largest manufacturing industry in the EU, generating 1.7 million jobs and indirect employment for more than 3 million people. In total, the EU produces 31 percent of the world's chemical; Germany's share is 26 percent in that, with only the USA and Japan producing more. 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. (Association of the German Chemical Industry).[1] In past several years, the industry has been downsizing, "right sizing," and producing new companies through small mergers, megamergers, and spin-offs. The new business reality gives every reason to believe there will be further consolidation and subsequent downsizing in the chemical industry (Millenium Special Report, 1999). This is also confirmed by the data for German chemical industry for 1992–2004 period, which tells us that the average size, defined as the number of employees of the firm, has decreased by about 47% (from 813 to 433).[2] This seems counterintuitive to the general trend of merges and acquisitions (Weston et al., 1999), and to the literature, which documents that relatively larger firms have better propensity to survive, and that economical/technological situation has put considerable pressure on smaller firms (Swift, 1999). Then the natural question arises: "Why small is beautiful?"

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

[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).

The globalization has taken great pace during the 1990s and the "whales" of the traditional German manufacturing industries had to respond to changing environment in which production process could be transferred to nearby low-cost geographical locations. Audretsch and Elston (2006) claim that the dominant (largest) firms have reacted by substituting of technology and capital by labor as well as by locating the new plants outside Germany. In the chemical sector during 1991–1995 the domestic employment decreased by 80 thousands, while 14 thousands jobs were created by chemical firms outside Germany; more specifically, during 1984–1994 Hoechst(BASF) decreased the number of jobs domestically from 99(86) to 73(66) thousands, while increased outside Germany from 79(30) to 92(40) thousands. These are however the flagships of the chemical industry, and such tendency cannot be easily translated to the all firms in the chemical industry. While it can be asserted that downsizing stems solely from the above-mentioned "changing rules of the game," this is an interesting and particular industry issue, which has to be addressed using rigorous statistical analysis. One intuitively comes up with an idea of scale economies (Baumol et al., 1988). In addition to such hypothesis, the "relative performance" argument comes into play. What if relatively smaller firm outperform relatively larger 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 (Alvarez and Crespi, 2003; Gumbau-Albert and Maudos, 2002; Torii, 1992) found that the technical efficiency increases with the size of the firm. On the other hand, in a larger firm much of the focus tends towards process, form, and bureaucracy and not towards results. Moreover, it is more difficult to keep all departments coordinated, that is, efficient (X-inefficiency, see Leibenstein, 1966). Additionally, the efficiency–size paradigm appears in the literature in the light of relationship between efficiency and market concentration (Nickell, 1996; Tsekouras and Daskalopoulou, 2006). Furthermore, that the data reveals reduction in size, provides a link to the stream of literature looking at the downsizing in the manufacturing industry and productivity. Baily et al. (1996) check the conventional faith that the rise in productivity and dowsizing are linked through some microeconomic mechanism. Authors find, though, that both dowsizers and upsizers increase in productivity and the relationship is quite complex and not clearcut. In their other paper, Baily et al. (2001) try to resolve the debate on cyclical nature of the labor productivity over time. They claim that the productivity of long-term downsizers tends to be quite considerable, much larger than that of long-run upsizers.

Although the focus of this paper is analysis of scale efficiency, "benchmarking" analysis plays important part. Therefore, the link to other studies looking at the productivity is valuable. The literature on productivity can be split into two subfields: (i) studies, which document the distribution of productivity and evolution of productivity and its growth over time, and (ii) studies, which address the question: What determines productivity and its growth? Bartelsman and Doms (2000) identify a story line, which helps understand literature on productivity. The first instance, firm's choices (innovative activity, input choices, and product output) generate a mechanism to turn inputs into outputs, i.e., the technology. Firm's choice interacts directly with market, the second instance, in a sense of sending as well as receiving demand/supply signals. Such market interaction in their turn generate productivity, the third instance. The literature has many examples of looking at various interactions between these three instances at different levels of aggregation. For example, how evolution of productivity affects entry and exits (Baldwin, 1995), or whether evolution of productivity goes procyclically (Baily et al., 2001). The current study is evolutionary in its nature. It tries to scrutinize the development of cross-firm performance comparison and size of the firm. In aforementioned story line, this work runs from the third to the first instance.

This paper is intended to shed light on downsizing in German chemical manufacturing industry during period 1992 through 2004 using modern frontier efficiency 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. The goal is to study the structural changes of the industry by looking at the distribution of the efficiencies and their changes over time. In this way the study adds to the literature on relation between firm performance and downsizing over time. The paper also attempts to quantify potential scale economies. More specifically, the focus is on the relationship between firm size and its performance by determining scale efficiency and the nature of scale inefficiency of the firms.

In the recent study of size efficiency of Indian banks Ray (2007) provides the estimates by how many units the size inefficient or "too large" bank could have been split so that sum of unilaterally produced outputs of resulting units is larger than the output of undivided bank. The analysis is based on the *sub-additivity* idea and his utilized methodology takes advantage of returns to scale estimation adopted from Maindiratta (1990). While this seems lucrative to quantify by *how much* does German chemical manufacturing deviate far from most productive scale size (Banker, 1984), several caveats have to be advanced, however. According to the implicit underlying methodological assumption the unit is split into identical sub-units. Economically, it is not realistic to emulate identical to initial unit organizational and operational structure of the sub-units. Moreover, additional transaction and break-up costs emerge, which would distort estimated optimal number of sub-units. From the methodological view point, it is assumed that "true" frontier is known, which has to be *estimated* in the reality (see section 2). Therefore, such "splitting" analysis will not be pursued here.

The paper unfolds as follows. Sections 2 provides an overview of methodology. Section 3 discusses data used in this study. Section 4 presents the empirical results and robustness checks, while section 5 concludes.

2 Methodology

This section provides an overview of methodology. The reader is referred to Färe (1988), Färe et al. (1994), 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, ming).

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. (1994) 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 under which portion of technology the unit is operating: increasing or decreasing returns to scale.

The second assumption concerns orientation of the analysis. Under output orientation, inputs are fixed on the observed level and outputs are boosted as much as possible within "best-practice" technology. Whereas, under input orientation, outputs are held constant and the inputs are reduced within "best-practice" technology. In the analysis of manufacturing firms it is intuitive to assume output orientation (e.g., Shiu, 2002), since resources are limited and not subject to a very quick change, while economic purpose is to produce as much as possible. It is especially true in the case of the growing German chemical industry.

2.1 Technical efficiency

For each firm j ($j = 1, \dots, N$) vector $x_j = (x_{j1}, \dots, x_{jP}) \in \Re^P$ denotes P inputs, vector $y_j = (y_{j1}, \dots, y_{jQ}) \in \Re^Q$ denotes Q outputs. The technology T identifies feasible combination of inputs and outputs,

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

and is fully characterized by its production possibility set $P(x)$,

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

The boundary of T can be assumed to exhibit three different types of returns to scale: Constant Returns to Scale (CRS), Nonincreasing Returns to Scale (NIRS), and Variable Returns to Scale (VRS).

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

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

is by construction 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 of production possibility set $P(x)$ or making it technically efficient. Depending on the assumption about the boundary of T, three distance functions are distinguished: $D^{CRS}(x, y)$, $D^{NIRS}(x, y)$, and $D^{VRS}(x, y)$.

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

$$\widehat{\mathrm{TE}}_j^o = \left[\max\left\{\theta\colon \sum_{j=1}^{N} z_j y_{jq} \geq y_{jq}\theta, \sum_{j=1}^{N} z_j x_{jq} \leq x_{jq}, z_j \geq 0\right\}\right]^{-1}, \qquad (4)$$

for $p = 1, \ldots, P$ and $q = 1, \ldots, Q$. The estimator of $P(x)$ is the smallest convex free-disposal hull that envelops the observed data, and upper boundary of which is a piece-wise linear estimate of the true best-practice frontier of $P(x)$. Equation (4) gives us constant returns to scale (CRS) specification. Other returns-to-scale are modeled by adjusting process operating levels z_j's; for modeling variable returns to scale (VRS) a convexity constraint is added, an $\sum_{j=1}^{N} z_j = 1$ equality,[3] while for modeling non-increasing returns to scale (NIRS) an $\sum_{j=1}^{N} z_j \leq 1$ inequality is added,[4] to linear programming problem in equation (4).

To facilitate the discussion, Figure 1 presents hypothetical one-input one-output production process with three different technologies CRS, VRS and NIRS. Intuitively, in Figure 1 the vertical distance from an observation (either (x_i, y_i) or (x_j, y_j)) to CRS/VRS/NIRS best-practice frontier stands for output-oriented technical efficiency under CRS/VRS/NIRS assumption. In a multi-dimensional case, the required distance is the radial path from an observation that is parallel to axes along which all outputs are measured.

2.2 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 *estimated* from a finite sample (in equation (4) from N observations) are subject to sampling variation of the estimated frontier (Simar and Wilson, 1998). The *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

[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, $\sum_{j=1}^{N} z_j$ 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.

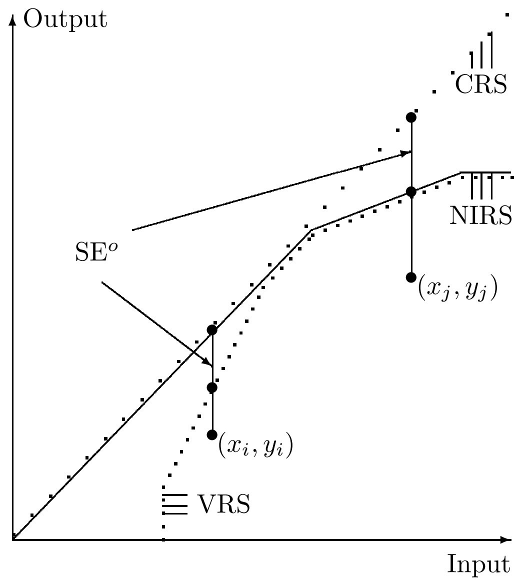

Figure 1: Output-oriented Technical and Scale Efficiency

enables to retrieve bias-corrected estimates of original (as in equation (4)) "overstated" technical efficiencies:

(i). Obtain efficiency scores $\widehat{\theta}_j$ as in equation (4) for each firm j, $j = 1, \ldots, N$.

(ii). Using a smooth bootstrap, generate θ_b^*, a random sample of size N $(j = 1, \ldots, N)$ from $\widehat{\theta}$:

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

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

where $\beta_1^*, \ldots, \beta_N^*$ is a bootstrap sample from the original efficiency estimates $\widehat{\theta}$, as in step (i), h is the smoothing parameter of the kernel density estimate of the original efficiency estimates $\widehat{\theta}$, and ϵ_j^*, $j = 1, \ldots, N$ are random draws from the standard normal. The smoothing parameter h is chosen via maximizing the likelihood cross-validation function and using reflection method described by Silverman (1986).

(iii). Compute y^*_{jb} for each j, $j = 1, \ldots, N$,

$$y^*_{jb} = \frac{\widehat{\theta}_j}{\theta^*_{jb}} y_j. \tag{7}$$

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

$$\widehat{\theta}^*_{jb} = \left[\max\left\{\theta\colon \sum_{j=1}^{N} z_j y^*_{jqb} \geq y_{jq}\theta, \sum_{j=1}^{N} z_j x_{jp} \leq x_{jp}, z_j \geq 0\right\}\right]^{-1}. \tag{8}$$

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

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

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

for each j, $j = 1, \ldots, N$.

2.3 Weighted technical efficiency

When number of observations is quite large to show result for each firm, it is convenient to 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 data on output prices are not available, the price independent weights are used, which are the sum of each firm's share of each output normalized by the number of outputs Q:

$$w_j = \frac{1}{Q}\left(\frac{y_{j1}}{\sum_{j=1}^{N} y_{j1}} + \frac{y_{j2}}{\sum_{j=1}^{N} y_{j2}} + \ldots + \frac{y_{jQ}}{\sum_{j=1}^{N} y_{jQ}}\right) = \frac{1}{Q}\sum_{q=1}^{Q} \frac{y_{jq}}{\sum_{j=1}^{N} y_{jq}} \tag{11}$$

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

2.4 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. Keeping in mind that distance can be *estimated* relative to three different assumed boundaries of T—CRS, NIRS, and VRS—the measures of scale efficiency,[5] originally proposed by Färe and Grosskopf (1985),

$$s(x,y) = \frac{D^{CRS}(x,y)}{D^{VRS}(x,y)}, \tag{12}$$

and

$$\eta(x,y) = \frac{D^{NIRS}(x,y)}{D^{VRS}(x,y)} \tag{13}$$

are used to facilitate the discussion on bootstrap test. If $s_j(x_j, y_j) = 1$, a firm (x_j, y_j) is scale efficient. If $s_j(x_j, y_j) < 1$, a firm (x_j, y_j) is scale inefficient due to operating under the decreasing returns portion of technology if $\eta_j(x_j, y_j) = 1$ or due to operating under the increasing returns portion of technology if $\eta_j(x_j, y_j) < 1$. From the viewpoint of hypothesis testing, the statistic which showed the best statistical properties is defined as,

$$\widehat{S}_{2n}^{CRS} = \frac{\sum\limits_{j=1}^{N} \widehat{D}_j^{CRS}(x_j, y_j)}{\sum\limits_{j=1}^{N} \widehat{D}_j^{VRS}(x_j, y_j)}, \tag{14}$$

This statistic represents the ratio of the average distances to VRS and CRS frontiers. If null hypothesis is true, then average distance between VRS and CRS frontiers is small. If alternative hypothesis is true, then distance between VRS and CRS frontiers on average is large—the null hypothesis is rejected if $\widehat{S}_{2n}^{CRS}$ is significantly less than 1.

Taking into account the importance of returns to scale assumption for DEA estimator, 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

[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.

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 estimate exactly by scale efficiency. Therefore, performing the individual returns-to-scale test is fairly important in case of scale efficiency analysis.

First, for each firm the null hypothesis of Test 1 that distance functions are equal under constant and variable returns to scale or $s_j(x_j, y_j) = 1$ against an alternative hypothesis that $s_j(x_j, y_j) < 1$ is tested. 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 1. The firm (x_q, y_q), for which this null hypothesis is rejected, $s_q(x_q, y_q) < 1$, is said to be scale inefficient. For all scale inefficient firms a Test 2 with H_0 that that distance functions are equal under nonincreasing and variable returns to scale or $\eta_j(x_j, y_j) = 1$ against H_1 that $\eta_j(x_j, y_j) < 1$ has to be performed. The Test 2 concludes that firm (x_w, y_w) is operating under increasing returns to scale (such as a firm (x_i, y_i) in terms of Figure 1) if $\eta_w(x_w, y_w)$ is significantly less than 1, and is operating under decreasing returns to scale (such as a firm (x_j, y_j) in terms of Figure 1) otherwise. All tests in this subsection are bootstrap based tests, built on prior works by Simar and Wilson (1998, 2000), are not described here in detail to conserve space. Interested readers are referred to the original paper by Simar and Wilson (2002) for more details.

3 Data

This study uses micro data from the German Cost Structure Census of manufacturing for the period of 1992-2004 for the chemical industry.[6,7] 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

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

[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.

with 1–19 employees.[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.

The basic summary statistics of output and inputs are presented in Table 1, the frequency by size categories appear in Table 2. The measure of output is gross production. This mainly consists of the turnover and the net-change of the stock of the final products. Excluded are the turnovers from activities that are classified as miscellaneous such as license fees, commissions, rents, leasing *etc.* because such revenue can not adequately be explained by the means of a production process.

Cost Structure Census contains information on 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, the inputs were aggregated 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),[10] (iii)

[8] The data for year 1994 is not available. For more details see Fritsch et al. (2004).

[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 and Nehring, 2005).

[10] Unfortunately Cost Structure Census does not give the number of hours worked, which is conventional to use as a proxy for labor. It does, however, give the number of employees, but it is not used in the analysis for the following reason. There is some evidence that manufacturing firms have increased its outsourcing—Grossman and Helpman (2005) claim

energy consumption, (iv) 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 the real terms, all inputs and output were deflated using the producer price index for the respective industry.[11]

4 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 reasons for downsizing behavior in the chemical industry ensued during period 1992 through 2004.

4.1 Technical efficiency

For each of twelve years under consideration the non-parametric test of returns to scale (see section 2, subsection 2.4) was performed in order to apply the appropriate DEA model. In all twelve cases the null hypothesis that the technology is constant returns to scale (Test 1) is overwhelmingly rejected.[12] Further, for each year the Test 2 was performed, 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, 0.179, 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, the bootstrap based bias-correction procedure following

that "... Firms seem to be subcontracting an ever expanding set of activities, ranging from product design to assembly, from research and development to marketing, distribution, and after-sales service." Using number of employees would belie important information about real amount of labor used in the generating value added. Moreover, using aggregate labor compensation enables to account for different qualities of labor.

[11] Meeting the demand of scientific community for microdata of official statistics in Germany, the Federal Statistical Office has established Research Data Centers (www.forschungsdatenzentrum.de) in March 2002 (Zühlke et al., 2004). Nowadays, analysis of the representative dataset can be accomplished at secured sites in sixteen different locations in Germany. All estimations for this paper were carried out at the German Research Data Center in Berlin using remote computation.

[12] In contrast, using parametric technique, Martín-Marcos and Suárez-Gálvez (2000) prove the predominance of constant returns to scale in Spanish manufacturing.

Simar and Wilson (1998) (see section 2, subsection 2.2) is applied.[13] The year by year summary statistics of the technical efficiency are presented in Table 3. The averages due to Färe and Zelenyuk (2003) of bias corrected technical efficiency scores by size categories appear in Table 4.

The most striking result is the high level of technical inefficiency of German manufacturing firms—up to thirty percent. The weighted mean was ranging moderately from 0.70 to 0.75, remaining quite low. This implies that the same inputs in the different years could have produced 25–30 percent more of the observed output if the inputs were employed by firm with *frontier* production technology. For example, Sena (2006) finds that average technical inefficiency of Italian manufacturing firms during 1989–1994 ranges from ten to nineteen percent for various industries. Additionally, 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 (i) unchanged technology and unchanged performance of the "average" firm, or (ii) changing of the performance in the same path as change of the underlying technology. Former argument has mixed evidence in the literature. On the one hand, technological progress did positively influence the performance of the firm in chemical industry (Swift, 1999; Weston et al., 1999). On the other hand, Bathelt (2000) finds out that despite the "computerization–of–production–process" tendency, the use of microelectronic equipment is largely exaggerated; its mostly sales routines, customer services, and production planning that benefit greatly from computers introduction. In addition, conventional (manual) control engineering is still used in about half of German chemical firms; the rest is evenly divided between fully automated and almost not equipped with computers. If instead the latter argument applies, firms were going hand in hand with technological improvement, but were always legging behind the technological change. In the literature such phenomenon is known as a "general purpose technology," which emphasizes that it takes time before newly

[13] Bias correction introduces additional noise (greater variance of bootstrapped scores), which might result in that the mean-square error of bias-corrected score is larger than that of simple DEA estimate. This is especially true for the multidimensional setting. Therefore Simar and Wilson (2007) propose not to use bias-correction unless $\frac{|\widehat{bias}_j|}{\sigma_j} > \frac{1}{\sqrt{3}}$ or more conservatively $\frac{|\widehat{bias}_j|}{\sigma_j} > \frac{1}{4}$; where σ_j is the standard deviation of bootstrapped efficiency scores, $\widehat{\theta}^*_{jb}$. In the sample used here, for 1992, for example the minimum, the mean, and the maximum of $\frac{|\widehat{bias}_j|}{\sigma_j}$ are 1.103, 2.038, and 2.940, respectively, which indicates not very large variance of bootstrapped scores introduced by bootstrap procedure. This makes using bias-correction legitimate for this particular case.

implemented technology can be utilized 100 percent efficiently (see Helpman and Rangel, 1999).

An alternative explanation for the finding that the technical efficiency of an "average" German chemical manufacturing firm was fairly stable over the period under consideration might be a failure to transition from rigid Fordist practices to flexible ones. Bathelt (2000) claims that the changes in production programs did not lead to greater flexibility. Firms did not seem to deviate from production of standardized in favor of specialized differentiated goods. Additionally, production programs on average have been mostly left unchanged than fundamentally reorganized.

Remarkably, a close look at the Table 4, which presents descriptive statistics of technical efficiency by size categories, reveals that in different years larger firms perform better or similar 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 an advantage of the largest size category. As a robustness check the order-alpha quantile-type frontier approach was applied to determine the effect of size on the efficiency of firms (Daouia and Simar, 2006). The partial frontier analyses back-up the conclusion that the size is a 'favorable' variable, implying that relatively larger firms (only starting from size "500 and more employees") are more technically efficient than smaller ones.[14]

The latter finding creates a puzzle, which bags for an explanation: larger firms in various years are on average more technically efficient, but data tells us that firms have been persistently downsizing. Does this frustrate the "the small is beautiful" argument? The answer is "no." Resolving this puzzle is the subject of the following subsection.

4.2 Scale efficiency

Previous subsection notices that the industry has *not* been operating under global constant returns to scale, meaning that scale inefficiency is present. That is why, current subsection performs an analysis of scale efficiency of German chemical manufacturing firms. Instead of estimating scale efficiency in accordance with equation (12) and (13) following Färe and Grosskopf (1985), the Test 1 and Test 2 are applied to individual firms (Simar and Wilson, 2002).

[14]The full set of results appears in Appendix A, which is available from author upon request.

Let us 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 5. The most remarkable finding is that the share of scale efficient has been showing strong tendency to increase: from 62 percent in 1992 to 68 percent in 2004. Such tendency was however unstable with peak in 1998: 81 percent. Repeating the exercise with overall size of the test of 10 percent did not bring any difference–the difference between sizes of individual tests when $\alpha_g = 0.05$ or $\alpha_g = 0.1$ is so small[15] that the conclusion that the share of scale efficient firms has been growing is robust: 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, the scale efficiency analysis in different size categories is important in the light of the "small is beautiful" argument. The frequencies of scale efficient firms are shown in Table 6 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 years and is either one or very close to one. Second, the middle size firms ("50 to 249 employees") have experienced the largest growth in the share of scale efficient firms, about 25 percent: from 74 to 92 percent in size category "50 to 99 employees", and from 50 to 58 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 gives even bigger rise to "the small is beautiful"–interpretation. The fact that the size of the firm have been gradually decreasing over the years (see Table 2), plus the fact that the share of scale efficient firms has been increasing shed light on three above-mentioned observations. Larger firms are not very likely to change their course: there is little evidence that large-volume production runs will be replaced by small-volume ones; at the same time, small and medium-sized firms are forced to redefine their market strategies and change the their production process in order to strengthen their competitiveness (Bathelt, 2000).

The nature of scale inefficiency is analyzed by perfoming 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

[15] The approach requires that the size of each of the n individual tests, α_l, be chosen much smaller than the global or overall size of the test, α_g. More specifically, $\alpha_l = 1-(1-\alpha_g)^{1/n}$. For example, $\alpha_l = 0.00007327$ for $n = 700$ and $\alpha_g = 0.05$; $\alpha_l = 0.0001505$ for $\alpha_g = 0.1$.

increase its size to be more scale efficient; if the null of the Test 2 is failed to be rejected then firm is operating under decreasing returns to scale portion of technology and has to decrease its size. Theoretically, firms strive to be scale efficient to enjoy most productive scale size (Banker, 1984) in the sense of being more productive. The nature of scale inefficiency is indicative of the direction of marginal rescaling that the firm should undertake in order to improve its productivity.

Table 7 superimposes results from Table 5 and presents the frequencies 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 1995, 1998 and 1999. The most remarkable finding, however, is that while a considerable portion of firms are scale inefficient (up to 38 percent in 1992, in the beginning of the period) the reason for that virtually *all*[16] of them is operating under decreasing returns to scale portion of technology. According to Table 7, from 99 to 100 percent of scale inefficient firms resemble firm i from Figure 1, and consequently had to downsize to get scale efficient—and this is exactly what they have been doing during the 1990s.[17]

These findings suggest that for German chemical manufacturing firms improving technical efficiency has *not* been the first priority during the 1990s. Instead, they have been paying special attention to establishment of an optimal scale, while technical efficiency has been supported on a certain level. This tendency can be clearly read from Tables 5 and 3. And since scale inefficient firms cared about being scale efficient and simultaneously operated under decreasing returns to scale, they have been reducing their size. At a certain level, this finding supports that of Baily et al. (2001) who stress that the productivity of long-term downsizers is much bigger than that of upsizers.

Why such excess capacities could have existed and/or could have been accumulated prior to the 1990s? The institutional features of the German financial system made it more lucrative to be large to have access to external funds. Audretsch and Elston (1997, 2006) argue that the so-called *Mittelstand* paradox in Germany—that the smaller firms have been growing more slowly—characterized German traditional manufacturing before the 1990s.

[16] Only in 1997 one firm out of 220 is scale inefficient due to IRS.

[17] Such closeness to 100 percent might elicit one's dubious feelings about the power of the test. Hence, I have looked at the raw, not bootstrapped values of η_j (equation (13)); they turned out to be approximately 0.98 on average. This is very close to 1 implying that on average distances to VRS and to NIRS frontiers are almost equal, which practically precludes IRS nature of scale inefficiency. Bootstrapped tests confirm this.

German policy makers tried to change this situation with introduction of the *Neuer Markt* in 1997, the new segment of Frankfurt exchange. It resulted in greater and more flexible financing for all smaller firms and not only those listed on the *Neuer Markt* (small new technology based enterprises). The authors find out that once financial restrictions were eliminated smaller firms grew even faster that larger ones.

Furthermore, the chemical firms in the Eastern Germany have been a particular case for a long time before the 1990s. Before Soviet Union collapsed, the Eastern German chemical industry has been operating on the planning principles. The scales of production were not justified economically, but rather just served some virtual goals. The major difficulties associated with industry were obsolete production technologies, the dominance of inefficient coal-based production, little variety of final products, to name a few. As a result of these problems and already existed overcapacities most firms had to reduce their production and employment to a minimum after unification with Western Germany (Bathelt, 1995).

Another reason is an international position, persistency and specialization of German chemical industry. It is strongly oriented toward international markets.[18] Moreover, chemical industry in Germany is concentrated around some historically established agglomerations such as Leverkusen–Köln–Düssedorf and Frankfurt-Wiesbaden (Freeman, 1990). The massproduction paid off quite well before the 1990s. However, during the 1990s the shift in the demand has been significant: it declined and became fastidious worldwide. People wanted ‘environmentally friendly’ goods. Yet health and environmental regulations have gotten really rigorous, which revealed that German chemical plants had excess capacities and had to modernize their production capacities.

Why economies of scale might be of such an importance to the German chemical industry? What about economies of scope? Bathelt (2000) identifies three types of German chemical firms: (i) semiflexible integrated firms, mainly medium-large and large sized, with main features being high degree of vertical and/or horizontal integration and *limited* product and process flexibility; (ii) conventionally specialized firms, mostly small and medium sized, which are characterized by a *low* degree of product and process flexibility; and (iii) flexible specialized firms, which are mostly small and can only be found in the narrow chemical subindustry (pigments, dyes, paints, and varnishes).[19] Except for the third type of firms, which tries to achieve economies of scope to adjust to market-segmentation tendencies, the first

[18] In 1994, 54 percent of total sales went for exports.

[19] These firms make up roughly 13 percent of all German chemical firms.

two care about economies of scale by various production activities and by producing relatively long-term homogeneous goods. This empirical evidence gives grounds to believe that economies of scale have implications for the German chemical manufacturing firms.

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 during the 1990s. The nature of scale inefficiency clearly renders an explanation for downsizing behavior in the industry. The explanation of the "small is beautiful" phenomenon proved robust over years.

4.3 Robustness Check

There are reasons to believe that pharmaceutical industry is quite dynamic and highly competitive in Germany, and therefore very efficient. German manufacturing pharmaceutical firms comprise about one fifths of all German chemical manufacturing firms. Hence, if pharmaceutical firms prove to behave differently, the conclusions of the paper are driven primarily by this subindustry. Thus, the check of the results for robustness is useful.

Table 8 presents distribution of bias corrected technical efficiency scores for all available years. The fourth column tells us that even if pharmaceutical industry was operating differently from the entire chemical industry, the differences are minor. Moreover, we observe the same trend as in Table 3, specifically, that the distribution is virtually the same in all years under inspection. The differences of technical efficiency scores for firms, which existed in adjacent years appear in Table 9. While the mean of differences is sometimes positive, sometimes negative it is very close to zero. Given, that the distribution is fairly symmetric (percentiles 5 and 95, 10 and 90, 25 and 75, respectively are almost identical in absolute terms) and that standard deviation is about 0.18 the average is not statistically different for zero. These tables suggest that pharmaceutical firms were repeating the tendency of the entire chemical industry.

Additionally, one might think that the findings are primarily driven by choice of output orientation of the analysis. Appendix B replicates the results of the study but assumes input orientation, i.e., that the input quantities are the primary decision variables. While the weighted mean of technical efficiency on average now is approximately five percent larger than that under output orientation assumption, the first and third quartile as well as the median are virtually unchanged. The shares of scale efficient firms has also increased somewhat. The only stable result, which is most important is that those firms that are inefficient are inefficient so due to operating under decreasing returns to scale portion of the technology.

Furthermore, it might seem possible that the high portion of scale inefficient firms operating under decreasing returns to scale is the results of the high ratio of the number of the used inputs to the number of the produced output. Therefore, instead of six inputs, the analysis was re-run, firstly, with only five essential inputs: Capital, Labor, Energy, Material, and External Services and, secondly, with only three inputs obtained by pooling Capital, Energy, Material into first variable, External Services and Other Inputs into the second, and Labor being the third.[20] Such constellations (Appendix C) only introduce greater volatility of the shares of scale efficient firms but do not change decreasing returns to scale argument.

Data Envelopment Analysis is criticized for being sensitive to outliers because it envelops all data points. More robust estimators based on partial frontiers such as order-m frontier (Cazals et al., 2002) and order-alpha quantile-type frontier (Daouia and Simar, 2006) were proposed in the literature. Instead of pursuing estimation of technical efficiency scores using these methods, an additional robustness check of the main results was performed by taking advantage of methodology to detect outliers based on these partial frontier approaches (Simar, 2003). The full set of results without outliers appears in Appendix D. In different years potential outliers comprised roughly 3.5 percent of the sample size ($n/\sqrt{n}$, see Simar (2003) for details). As expected, leaving outliers out makes technical efficiency scores on average slightly larger, but not significantly: about 1–2 percent. The shares of scale efficient firms got larger, which means outlier detection methodology might have flagged scale inefficient firms. What remains robust, though, is the finding that the share of scale efficient firms has been increasing and, except for one firm in 1999, the nature of firms' scale inefficiency is production under decreasing returns to scale.

5 Concluding remarks

The German chemical manufacturing industry has been marked by major downsizing during 1992 to 2004. Using modern efficiency analysis techniques, this paper tries to identify reasons for aggregate tendency of firms to become smaller, the so called "small is beautiful" phenomenon.

Interestingly, the level of technical inefficiency is rather high—25 to 30 percent. Moreover, the firms have been persistently inefficient—during 1992 through 2004 the parameters of technical efficiency distribution were virtually the same in different years. The share of scale efficient firms has increased from 62 in 1992 to 68 percent in 2004 during the period under consideration.

[20] It is feasible since the inputs are in real monetary terms.

These are small firms, which 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, *all* firms are inefficient due to operating under decreasing returns to scale; they had to downsize to become more scale efficient. These findings rationalize the fact that firms have been continuously becoming smaller during 1992 through 2004.

The results have to be taken cautiously because of an intrinsic limitation of the data. While larger firms (more than 500 employees) are fully included in the sample, the smaller firms are included only as a random sample, which is considered representative for certain size category. Therefore, small firms are underrepresented, which might lead to some distortion of results. The size of such distortion, if any, is not possible to evaluate within existing data-set.

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 under which portion of technology firm is operating, and which implication does it have for decision about choosing the size of the firm. The analysis suggests that middle size firms, 50 to 249 employees, are most successful if technical and scale efficiency performance are analyzed in complex.

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Tables

Table 1: Output and Inputs: Summary Statistics, 1992-2004, excluding 1994

Year	N	cv	skewness	kurtosis	Mean	Q1	Median	Q3
Output								
1992	726	4.8	11.9	163.1	211227	9556	32291	105734
1993	695	4.7	11.5	151.6	201254	10088	30628	104326
1995	857	5.0	13.3	207.9	192545	11193	28973	91114
1996	843	4.8	13.5	216.6	194125	11237	28873	97709
1997	848	4.6	14.7	259.1	201217	11938	33325	103429
1998	814	4.5	14.7	256.0	205566	13101	36682	119755
1999	835	4.4	14.6	256.6	203617	14599	36467	131189
2000	819	4.4	14.2	243.7	231730	15608	37957	137831
2001	794	4.2	13.6	227.4	238612	17076	40720	144059
2002	784	4.3	14.1	237.5	227938	17603	42471	153535
2003	901	4.3	13.8	235.9	206873	15869	39053	120732
2004	881	3.9	13.1	241.3	218410	16955	40884	128955
Material inputs								
1992	726	3.9	9.2	101.5	76094	3610	11916	44648
1993	695	3.9	9.2	100.7	69872	3873	11297	39298
1995	857	4.0	10.4	132.7	72361	4439	11518	40527
1996	843	3.7	10.0	125.9	71357	4175	11540	40724
1997	848	3.6	10.7	151.7	77671	4408	13061	44486
1998	814	3.3	10.6	151.0	78033	5145	14800	50730
1999	835	3.4	10.6	156.7	79431	5393	14610	51340
2000	819	3.7	11.8	190.5	96394	5615	15913	58409
2001	794	3.5	11.3	176.9	97227	6202	17676	63914
2002	784	3.4	11.0	170.6	92073	6397	18628	64996
2003	901	3.7	12.1	192.1	83899	5440	15940	53414
2004	881	3.7	11.8	189.7	89703	5775	17206	54320
Labor compensation								
1992	726	5.6	13.0	189.4	69946	2666	7639	29511
1993	695	5.6	12.7	179.6	69790	2925	7730	29206
1995	857	5.9	14.4	231.7	58063	2856	7064	23952
1996	843	5.7	14.2	228.2	59243	2950	7338	25705
1997	848	5.4	15.8	289.4	55749	3260	7753	25736
1998	814	5.2	15.2	268.9	57408	3504	8761	28006
1999	835	5.0	15.0	262.6	57850	3716	9692	30491
2000	819	5.0	15.0	262.2	58331	3862	9955	30455
2001	794	4.8	14.0	232.6	60383	4298	10843	32079
2002	784	4.9	14.6	247.6	57650	4630	11567	32512
2003	901	4.9	14.9	272.9	54424	4052	9648	28459

Continued on Next Page…

Table 1 – Continued

Year	N	cv	skewness	kurtosis	Mean	Q1	Median	Q3
2004	881	4.5	16.0	341.5	54170	4152	9389	29590
Energy consumption								
1992	726	7.3	15.5	277.7	10032	124	462	1994
1993	695	7.5	15.3	268.8	9439	125	455	2122
1995	857	7.6	16.7	323.2	7973	132	447	1911
1996	843	7.7	17.9	376.3	8146	130	451	1906
1997	848	7.9	20.7	495.8	8154	131	441	2055
1998	814	7.2	19.1	427.0	8190	138	498	2128
1999	835	4.9	11.5	167.6	6931	152	528	2044
2000	819	5.1	11.5	167.1	7616	159	538	2181
2001	794	5.3	12.6	195.8	8660	188	601	2440
2002	784	5.3	12.3	186.0	8539	183	611	2428
2003	901	5.8	15.6	296.3	7633	157	507	2461
2004	881	5.2	13.0	218.5	7765	166	545	2613
Capital								
1992	726	5.3	11.9	161.3	17745	620	1803	6419
1993	695	5.3	11.6	153.1	18046	672	1986	6911
1995	857	5.4	12.8	187.0	14905	654	1795	5638
1996	843	5.2	12.5	180.5	15186	659	1753	5977
1997	848	4.9	13.7	228.6	13985	677	1787	6272
1998	814	4.7	13.9	235.6	14342	712	1972	6839
1999	835	4.6	13.7	231.0	14831	904	2127	7218
2000	819	4.6	13.4	221.7	15225	951	2213	6996
2001	794	4.5	13.1	211.2	15620	989	2417	7102
2002	784	4.7	13.5	222.2	15230	992	2532	7429
2003	901	4.8	14.0	242.4	14202	845	2287	6479
2004	881	4.0	12.0	201.2	13617	888	2314	6372
External services								
1992	726	6.2	12.4	182.7	12663	175	747	3217
1993	695	6.1	12.4	183.6	11597	184	728	2884
1995	857	7.3	16.3	303.7	10650	186	713	2969
1996	843	7.4	15.6	276.1	12579	200	740	2925
1997	848	7.5	17.2	329.3	12926	217	796	3295
1998	814	7.3	18.0	360.8	13106	240	878	3903
1999	835	6.7	17.2	340.3	13052	277	1082	4506
2000	819	7.0	17.1	321.0	14385	300	1143	4588
2001	794	7.6	17.8	349.5	15634	342	1182	4850
2002	784	7.2	17.0	319.5	13833	405	1257	4655
2003	901	6.0	15.1	270.5	12506	300	1017	4213
2004	881	5.6	16.7	356.5	11818	310	1032	4212
"Other" inputs related to production								
1992	726	4.5	11.0	144.2	37904	1260	4348	18097

Continued on Next Page…

Table 1 – Continued

Year	N	cv	skewness	kurtosis	Mean	Q1	Median	Q3
1993	695	4.4	10.1	122.2	38917	1340	4201	18227
1995	857	4.7	11.6	160.4	35912	1346	3883	15969
1996	843	4.7	11.8	167.9	38437	1414	3770	17788
1997	848	4.5	13.3	229.2	38268	1386	4213	17980
1998	814	4.5	13.1	228.1	40584	1585	4615	20576
1999	835	5.6	17.4	374.4	44078	1728	4679	19742
2000	819	5.0	13.3	220.4	45376	1831	5062	19941
2001	794	5.5	15.5	291.8	48938	2070	5256	22180
2002	784	5.9	16.9	331.1	45940	2190	5642	23639
2003	901	5.4	13.6	216.6	41305	1843	4938	17954
2004	881	5.1	12.4	196.7	45081	1947	5162	18497

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

Table 2: Frequency of Firms, 1992 through 2004, excluding 1994.

	1992			1993			1995			1996			1997			1998		
	N	%	% c.	N	%	% c.	N	%	% c.	N	%	% c.	N	%	% c.	N	%	% c.
< 49	191	26.3	26.3	176	25.3	25.3	251	29.3	29.3	242	28.7	28.7	248	29.3	29.3	218	26.8	26.8
50-99	133	18.3	44.6	143	20.6	45.9	176	20.5	49.8	178	21.1	49.8	165	19.5	48.7	169	20.8	47.5
100-249	151	20.8	65.4	146	21.0	66.9	186	21.7	71.5	184	21.8	71.7	191	22.5	71.2	182	22.4	69.9
250-499	93	12.8	78.2	85	12.2	79.1	96	11.2	82.7	91	10.8	82.4	86	10.1	81.4	91	11.2	81.1
500-999	65	9.0	87.2	63	9.1	88.2	71	8.3	91.0	67	8.0	90.4	73	8.6	90.0	77	9.5	90.5
> 1000	93	12.8	100	82	11.8	100	77	9.0	100	81	9.6	100	85	10.0	100	77	9.5	100
total	726	100		695	100		857	100		843	100		848	100		814	100	

	1999			2000			2001			2002			2003			2004		
	N	%	% c.	N	%	% c.	N	%	% c.	N	%	% c.	N	%	% c.	N	%	% c.
< 49	189	22.6	22.6	180	22.0	22.0	162	20.4	20.4	151	19.3	19.3	207	23.0	23.0	194	22.0	22.0
50-99	188	22.5	45.2	185	22.6	44.6	186	23.4	43.8	180	23.0	42.2	223	24.8	47.7	218	24.7	46.8
100-249	197	23.6	68.7	198	24.2	68.7	194	24.4	68.3	201	25.6	67.9	211	23.4	71.1	217	24.6	71.4
250-499	103	12.3	81.1	106	12.9	81.7	103	13.0	81.2	108	13.8	81.6	114	12.7	83.8	112	12.7	84.1
500-999	79	9.5	90.5	74	9.0	90.7	76	9.6	90.8	74	9.4	91.1	77	8.6	92.3	76	8.6	92.7
> 1000	79	9.5	100	76	9.3	100	73	9.2	100	70	8.9	100	69	7.7	100	64	7.3	100
total	835	100		819	100		794	100		784	100		901	100		881	100	

[2a] ‘N’ is number of firms; ‘%’ is the share of all firms, ‘% c.’ is the cumulative share of all firms.

Table 3: Technical Efficiency: Summary Statistics, 1992-2004, excluding 1994.[3a]

Year	N	Mean[3b]	St.d.	Coef. of Var.	Skewness	Kurtosis	min	Q25	Median	Q75
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
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

[3a] Technical Efficiency are bias corrected efficiency scores following Simar and Wilson (1998).
[3b] Averages are due to Färe and Zelenyuk (2003).

Table 4: Averages[4a] of Technical Efficiency and Number of Firms by Size Categories, 1992-2004, excluding 1994.

	1992		**1993**		**1995**		**1996**		**1997**		**1998**	
Size Category	N	mean	N	mean	N	mean	N	mean	N	mean	N	mean
less than 49 employees	191	0.66	176	0.65	251	0.67	242	0.67	248	0.7	218	0.71
50-99 employees	133	0.71	143	0.69	176	0.68	178	0.68	165	0.68	169	0.69
100-249 employees	151	0.73	146	0.71	186	0.73	184	0.72	191	0.7	182	0.7
250-499 employees	93	0.72	85	0.7	96	0.74	91	0.73	86	0.74	91	0.73
500-999 employees	65	0.73	63	0.71	71	0.76	67	0.76	73	0.77	77	0.76
more than 1000 emp.	93	0.74	82	0.74	77	0.75	81	0.75	85	0.74	77	0.75
total	726	0.74	695	0.73	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

[4a] Averages are due to Färe and Zelenyuk (2003).

Table 5: Frequency of Scale Efficient Firms (for which Test 1 is not rejected).[5a]

year	Total N	N of SE Firms[5b]	N of SE Firms, %
1992	726	451	0.621
1993	695	441	0.635
1995	857	536	0.625
1996	843	547	0.649
1997	848	628	0.741
1998	814	658	0.808
1999	835	649	0.777
2000	819	555	0.678
2001	794	574	0.723
2002	784	561	0.716
2003	901	679	0.754
2004	881	598	0.679

[5a] The size of the test is 5 or 10 per cent (see footnote 15).
[5b] 'SE' stands for scale efficient.

Table 6: Frequency of Scale Efficient Firms by Size Categories, 1992-2004, excluding 1994.

	1992		1993		1995		1996		1997		1998	
Size Category	N	freq.[6a]	N	freq.	N	freq.	N	freq.	N	freq.	N	freq.
less than 49 employees	191	0.88	176	0.89	251	0.82	242	0.83	248	0.81	218	0.88
50-99 employees	133	0.38	143	0.36	176	0.45	178	0.31	165	0.64	169	0.78
100-249 employees	151	0.15	146	0.15	186	0.19	184	0.13	191	0.32	182	0.54
250-499 employees	93	0.16	85	0.16	96	0.20	91	0.16	86	0.27	91	0.27
500-999 employees	65	0.08	63	0.10	71	0.10	67	0.15	73	0.14	77	0.10
more than 1000 emp.	93	0.12	82	0.10	77	0.13	81	0.09	85	0.09	77	0.12
total	726	0.37	695	0.37	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

[6a] ‘freq’ stands for frequency in per cent.

Table 7: 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, excluding 1994.[7a]

	scale efficient			scale inefficient		
year	Total N	N of SE	N of SE, %	N of SI	Due to DRS	Due to DRS, %[7b]
1992	726	451	0.621	275	275	1
1993	695	441	0.635	254	254	1
1995	857	536	0.625	321	321	1
1996	843	547	0.649	296	296	1
1997	848	628	0.741	220	219	0.99
1998	814	658	0.808	156	156	1
1999	835	649	0.777	186	186	1
2000	819	555	0.678	264	264	1
2001	794	574	0.723	220	220	1
2002	784	561	0.716	223	223	1
2003	901	679	0.754	222	222	1
2004	881	598	0.679	283	283	1

[7a] The size of the test is 5 or 10 per cent (see footnote 15).
[7b] 'SE' stands for scale efficient; 'SI' stands for scale inefficient; 'DRS' stands for decreasing returns to scale.

Table 8: Distribution of technical efficiency, 1992-2004, excluding 1994.[8a]

year	N	mean	weighted mean[8b]	sd	cv	p5	p10	p25	p50	p75	p90	p95
1992	142	0.620	0.752	0.147	0.237	0.387	0.417	0.515	0.615	0.750	0.808	0.838
1993	146	0.623	0.733	0.143	0.230	0.379	0.418	0.507	0.629	0.738	0.812	0.830
1995	165	0.634	0.744	0.138	0.218	0.395	0.455	0.539	0.636	0.732	0.831	0.858
1996	160	0.635	0.754	0.139	0.219	0.378	0.456	0.541	0.639	0.749	0.821	0.841
1997	166	0.625	0.744	0.138	0.221	0.386	0.461	0.538	0.625	0.734	0.796	0.850
1998	152	0.629	0.731	0.139	0.222	0.356	0.440	0.548	0.637	0.722	0.796	0.846
1999	160	0.649	0.750	0.130	0.200	0.417	0.473	0.546	0.657	0.750	0.827	0.840
2000	155	0.642	0.761	0.141	0.220	0.393	0.445	0.545	0.654	0.756	0.821	0.844
2001	157	0.649	0.759	0.134	0.207	0.414	0.470	0.560	0.656	0.763	0.824	0.841
2002	145	0.645	0.755	0.129	0.201	0.418	0.486	0.553	0.652	0.744	0.819	0.843
2003	165	0.623	0.753	0.147	0.236	0.359	0.427	0.514	0.628	0.735	0.811	0.861
2004	159	0.622	0.731	0.149	0.239	0.357	0.435	0.525	0.624	0.753	0.804	0.846

[8a] Technical Efficiency are bias corrected efficiency scores following Simar and Wilson (1998).
[8b] Averages are due to Färe and Zelenyuk (2003).

Table 9: Distribution of difference technical efficiencies for firms, which exist in adjacent years, 1992-2004, excluding 1994.[9a]

difference	N	mean	sd	p5	p10	p25	p50	p75	p90	p95
1993 / 1992	142	0.005	0.187	-0.270	-0.204	-0.105	0.002	0.123	0.218	0.309
1995 / 1993	146	0.024	0.186	-0.254	-0.225	-0.118	0.004	0.144	0.288	0.353
1996 / 1995	160	-0.002	0.194	-0.322	-0.263	-0.120	-0.005	0.125	0.227	0.324
1997 / 1996	160	-0.005	0.184	-0.321	-0.242	-0.145	-0.011	0.131	0.227	0.306
1998 / 1997	152	-0.011	0.196	-0.383	-0.272	-0.130	-0.001	0.135	0.216	0.254
1999 / 1998	152	0.024	0.189	-0.269	-0.207	-0.110	0.035	0.138	0.270	0.381
2000 / 1999	155	-0.008	0.184	-0.346	-0.278	-0.099	0.008	0.099	0.219	0.328
2001 / 2000	155	0.008	0.181	-0.293	-0.238	-0.094	0.010	0.117	0.234	0.310
2002 / 2001	145	-0.012	0.189	-0.353	-0.251	-0.123	-0.003	0.115	0.225	0.278
2003 / 2002	145	-0.008	0.186	-0.338	-0.233	-0.125	0.010	0.098	0.225	0.294
2004 / 2003	159	-0.002	0.176	-0.309	-0.217	-0.103	0.009	0.094	0.228	0.306

[9a] Since data for 1994 are unavailable, we treat 1993 and 1995 as adjacent.