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– An Empirical Investigation

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What Causes Cross-industry Differences of Technical Efficiency? – An Empirical Investigation*

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November 2004

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Abstract

Using micro-level panel data of about 35,000 firms from the German Cost Structure Census, we analyze the differences of technical efficiency across industries. Technical efficiency is estimated by firms' fixed effects. One striking result is that the distribution of technical efficiency across industries is positively skewed. This is because the efficiency distribution is truncated at the lower end due to the least efficient firms which exit the market. We investigate the causes of technical efficiency differences across industries. Our econometric analyses provide evidence that capital and human capital intensity, the degree of vertical specialization as well as new firm formation rate are important for explaining the average technical efficiency of an industry.

JEL classification: D24, L10, L11

Keywords: Technical efficiency, cross-industry study, efficiency distribution

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Contents

1. Introduction

Firms are not equally efficient. Empirical studies find indeed considerable variation of the efficiency of firms within (Fritsch & Stephan, 2004b) as well as across industries. [1] An important category in this respect is technical efficiency. Technical efficiency is defined as the generation of the maximum output from a given bundle of resources. A firm is technically inefficient if it fails to obtain the maximum possible output. The reasons for technical inefficiency can be manifold and comprise all kinds of 'mismanagement' such as inappropriate work organization, deficiencies in the choice and use of technology (cf. Fritsch & Mallok, 2002), bottlenecks with regards to material flows etc. In this paper we investigate the extent and the causes of inter-industry differences of technical efficiency. We have two main presumptions regarding the determinants of average technical efficiency that we aim to test empirically. The first is that accumulation of both tangible and intangible capital (human and knowledge capital) is conducive for a high level of technical efficiency. The second is that the average level of technical efficiency is higher in more competitive industries because firms with inefficient practices (slack and suboptimal use of inputs) are forced to improve their performance or to exit the market.

Our study contributes to the literature on the determinants of technical efficiency in several respects. First, we use a unique micro panel of about 35,000 German enterprises over the period 1992 to 2002. This data contains rich information about the cost structure for each of the firms and can be regarded as representative for the German manufacturing sector. Second, our approach is not based on a stochastic frontier production function like the majority of previous studies, rather we estimate technical efficiency as firm-specific fixed effects. Since this method does not require an a priori assumption

[1] See for example Caves & Barton (1990), Mayes, Harris & Lansbury (1994) and the contributions in Caves (1992) and in Mayes (1996). For an overview see Caves & Barton (1990, 15-20) and Caves (1992).

about the distribution of technical efficiency within an industry it is less restrictive. Furthermore, we do not need to assume that a firm's level of technical efficiency is uncorrelated with its factor inputs. Thirdly, we examine the causes of cross-industry differences of technical efficiency not only for the average value but also for the relatively efficient and the relatively inefficient firms, i.e. at the upper and lower end of the efficiency distribution of the industry.

One striking result of our study is that the distribution of average technical efficiency across industries is truncated at the lower part, and, hence, that the efficiency distribution is positively skewed or “skewed to the right” in most of the industries. This means that if the values of a distribution are in increasing order from the left to the right, a positively skewed distribution has the longer tail at the right side where the values are above the median. This result is noteworthy because most previous studies have (implicitly) assumed a negatively skewed distribution of technical efficiency across firms by applying a stochastic frontier model.[2] Given that the distribution is not negatively skewed in at least 95 percent of the industries, we suspect that the results of analyses based on a stochastic frontier function are probably misleading.

The remainder is organized as follows. Methodical issues in the assessment of technical efficiency are discussed in more detail in Section 2. Section 3 introduces the data and our empirical approach for measuring technical efficiency. Results of the estimated production function are reported in Section 4. Section 5 gives an overview on the extent of efficiency variation between industries. Section 6 reviews the main hypotheses on the causes of cross-industry efficiency variation. Results of the empirical analysis are presented and discussed in Section 7. Finally, Section 8 draws some conclusions and indicates directions for further research.

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[2] If the distribution is negatively skewed the longer tail is at the left side with values below the median.

2. Measuring technical (in-)efficiency

An assessment of technical (in-)efficiency of firms or industries requires the measurement of efficiency and the identification of a point of reference for evaluating the relative efficiency level of the unit under inspection. This can be done in a number of different ways (see Mayes, Harris & Landsbury, 27-54, for an overview). All these approaches define technical efficiency as the highest output level that can be attained by using a given combination of inputs. Any deviation from this maximum is then regarded as inefficiency. The maximum technical efficiency in an industry can be directly obtained by estimating a frontier production function, i.e. a function for the input-output relationship of the most efficient firm(s).

The majority of analyses that have applied this approach estimated a stochastic form of a frontier production function. A stochastic frontier production function is based on the assumption that the input-output relationship is not completely deterministic, but subject to influences that appear to be erratic. This approach of estimating maximum technical efficiency has the advantage that extreme outliers of highly efficient firms or data errors do not automatically serve as the efficiency benchmark. However, in order to separate the impact of technical inefficiency from the ordinary stochastic effects, an a priori assumption about the distribution of technical inefficiency is required. Because the factual efficiency of a firm cannot exceed the possible maximum, the distribution must be truncated at this maximum. The usual hypothesis in this respect is that most firms cluster close to the efficiency frontier and that their frequency decreases with rising inefficiency. Such a distribution of the residuals is negatively skewed, i.e. it has the 'longer tail' on the low efficiency side. If the distribution of residuals is not skewed but symmetric, the level of technical inefficiency in the respective industry is assumed to be not significant.[3] A positively skewed distribution of residuals is

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[3] A measure of skewness can then be used as an indicator for the level of technical inefficiency in the respective industry; cf. Caves & Barton (1990, 47-49) or Mayes, Harris & Lansbury (1994, 50-52).

not consistent with the underlying assumptions. In an analysis of technical inefficiency within German manufacturing industries based on a deterministic production function, Fritsch & Stephan (2004b) found that in about 95 percent of the industries the distribution was skewed to the right.[4] This implies that for the overwhelming majority of industries an assessment of technical efficiency by means of a stochastic production frontier function is based on an inappropriate assumption so that the results could be misleading.

In order to assess technical efficiency in our sample of firms, we estimate a deterministic production function of the Cobb-Douglas type[5] with panel data for firms. This means that we avoid any a priory assumption about the distribution of technical efficiency as would be necessary when estimating a stochastic frontier production function. The production function can be written as

$$(1) \quad \ln y_{it} = \ln \alpha_i + \lambda_{it} + \sum \beta_k \ln x_{kit} + \varepsilon_{it}\,,\ k = 1,\ldots,p,\ i = 1,\ldots,N,\ t = 1,\ldots,T.$$

The term y_{it} represents output of firm *i* in period *t*, x_{kit} denotes production input *k*, β_k gives the output elasticity of input k, λ_t represent a time-specific effect, and α_i stands for a specific firms' technical efficiency. There are *N* firms and T_i observations for each firm.

[4] All the industries were from manufacturing. The analysis was based on the same data as is used in this paper.

[5] Attempts of estimating other types of production functions did not lead to satisfactory results. Estimates of a translog-type of production function frequently had rather implausible estimates (e.g. negative elasticities of production for certain inputs or scale elasticities larger than one). We suspect that the problems we experienced in estimating such other forms of production function than Cobb-Douglas were caused by the relatively high number of different inputs we are using and the statistical relationships between these inputs. Non-linear forms of a production function, e.g. CES, could not be estimated due to computational limitations of processing such estimations with the large number of firms we have in our data.

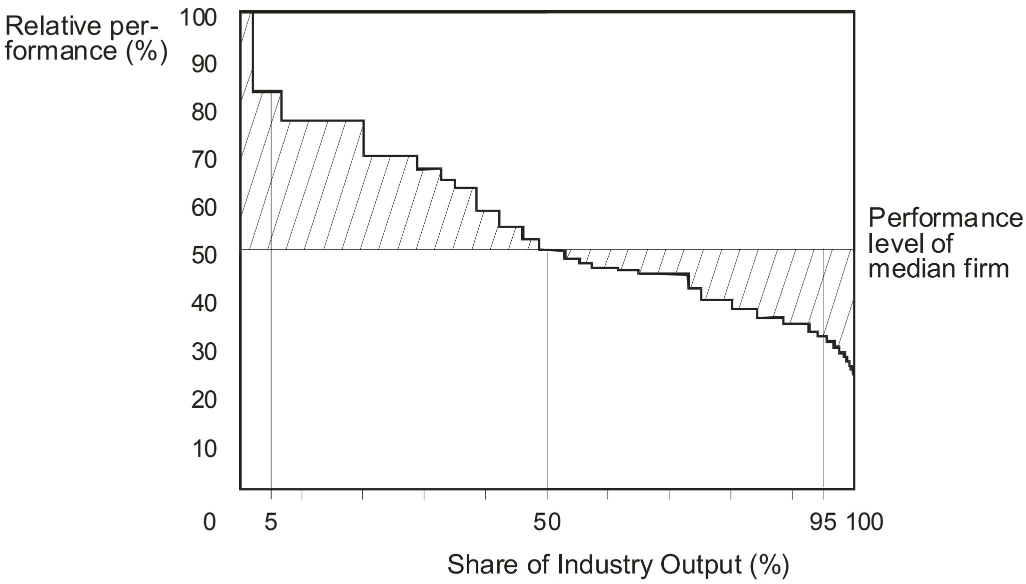

Figure 1: The efficiency distribution curve

Like Schmidt & Sickles (1984), we use the fixed-effects of firms as measures of technical efficiency. Since our approach is based on micro-data of individual firms, we obtain the distribution of technical efficiency estimates for each industry. Therefore it is possible to use a novel concept for measuring an industries' technical efficiency that is based on this distribution as described by the efficiency distribution curve. Figure 1 shows an example of the efficiency distribution curve for a (fictive) sample of firms in a particular industry with diverging efficiency levels (see also, Fritsch & Stephan, 2004b).[6] In this graph the firms are arranged according to their efficiency in descending order, starting with the most efficient firm. This most efficient firm constitutes the 100 percent benchmark for measuring relative technical efficiency of the other firms in the respective industry. Hence, efficiency of a firm is measured in relation to the value of the most efficient firm that represents the 100 percent value in this distribution. The length of the line for each firm corresponds to the relative size measured as share of gross production in the respective

[6] This exposition is inspired by diagrams in Salter (1969). Salter displayed productivity levels of firms in ascending order, starting with the least efficient firm.

industry (see Figure 1).[7] Small firm are accordingly represented by short lines, and large firms by longer lines. The resulting curve provides an informative portrayal of the distribution of efficiency within the respective industry.[8]

For the econometric analyses of cross-industry differences, average technical efficiency is computed at the 5 percent, 50 percent and at the 95 percent output level of each industry. Thus, we compare not only the average (median) efficiency level across industries, but also the relatively high and relatively low efficient firms.

Another important type of efficiency – allocative efficiency – concerns the choice of inputs. A firm is allocatively inefficient if the input combination is not optimal, given input prices and their marginal productivity of the different inputs in the production process.[9] A firm is allocatively efficient but technically inefficient if it chooses an optimal input combination but does not attain the highest possible isoquant of its production function (see Badunenko, Fritsch & Stephan, 2004).

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[7] Other possible measures of size to be used here are the number of employees and the volume of turnover that represents the importance of the relevant firm on the market. The number of employees is highly correlated with gross production and measures virtually the same thing, i.e. the level of economic activity in the firm. Using the volume of gross production or the amount of turnover as a measure of size may lead to considerably diverging results according to the firms' share of value added. If firms differ with regard to their vertical range of manufacture, turnover does not provide comparable information about the amount of economic activity. A further advantage of gross production as a measure of size is that gross production is not affected by stock-keeping behavior.

[8] The efficiency distribution curve can be used to derive a measure of efficiency heterogeneity within an industry, that accounts for the relative size of the individual firms, and that is also rather robust with regard to extreme values. This measure is defined as the area between the efficiency distribution curve and the efficiency level of the median output share firm in the industry (the shaded area in Figure 1). We label this measure *h-area*, where *h* stands for heterogeneity (cf. Fritsch & Stephan, 2004a, 2004b). In contrast to other measures of heterogeneity such as the standard deviation or the coefficient of variation, this area measure is sensitive to the size of the firms. For example, it takes into account whether the highly efficient firms have a relatively large share or only a small share of the industries' total output. This implies that the measure is reasonably robust with regard to small firms with extreme values that may not be considered as being representative of the industry.

[9] See Caves & Barton (1990, 9-11) or Mayes, Harris & Lansbury (1994, 12-26). The concept of technical inefficiency was introduced by Farrell (1957).

3. Data and measurement issues

Our estimates of firm-level efficiency are based on micro data of the German Cost Structure Census[10] of manufacturing for the period 1992-2002. Most of the other variables used in the empirical analysis are also obtained from this data unless indicated otherwise. The Cost Structure Census is raised and compiled by the German Federal Statistical Office (Statistisches Bundesamt). The survey comprises yearly information of all large German manufacturing firms with 500 and more employees. In order to limit the reporting effort for the smaller firms to a reasonable level, firms with 20-499 employees are included as a random sample that can be assumed representative for this size category as a whole. Firms with less than 20 employees are not included.[11] As

Table 1: Frequency of firms with regard to the numbers of observations in the sample

Number of observations (years)	*Number of firms*	*Share of all firms (percent)*	*Cumulated share of all firms (percent)*
2	10,384	29.4	29.4
3	5,635	15.96	45.36
4	4,948	14.01	59.37
5	4,537	12.85	72.22
6	3,737	10.58	82.8
7	1,780	5.04	87.84
8	1,056	2.99	90.83
9	1303	3.69	94.52
10	439	1.24	95.76
11	1496	4.24	100
Total	35,315	100	–

[10] Aggregate figures are published annually in Fachserie 4, Reihe 4.3 "Kostenstrukturerhebung im Verarbeitenden Gewerbe" of the German Statistisches Bundesamt.

[11] Beginning with the year 2001 the data also contains firms with 1-19 employees. These firms are, however, not included in our analysis because due to a rotating sampling scheme only one observation is available for most of these small firms.

a rule, the smaller firms report for four subsequent years and are then substituted by other small firms (rotating panel).[12] Because the estimation of firm-specific fixed effects requires at least two observations, firms with only one observation are excluded in our sample that comprises a total of about 35,000 firms. Table 1 shows the frequency of firms with different numbers of observations in our data set.

Our measure of output is gross production. This comprises mainly the turnover plus the net-change of the stock of final products. We do not include turnover from activities that are classified as miscellaneous such as license fees, commissions, rents and leasing etc. because we assume that such revenue can only be poorly explained by means of a production function. Our data contains information for a number of input categories. 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 wagework, external maintenance and repair, tax depreciation of fixed assets, subsidies, rents and leases, insurance costs, sales tax, other taxes and public fees, interest payments on outside capital as well as "other" costs for instance license fees, bank charges, postage or expenses for marketing and transport. Further information available in the Cost Structure Census is industry affiliation, location of headquarter, stock of raw materials, of goods for resale and of final output, R&D expenditure and number of R&D employees.[13] The information on employment comprises the number of active owners, the number of employees, of trainees, of part-time employees, of home workers and the number of temporary workers.

Some of the cost categories like expenditure for external wagework 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. Because all

[12] Due to mergers or insolvencies some firms have less than four observations. Note, however, that firms are legally obliged to respond to the Cost Structure Census, so there are actually no missing observations due to non-response.

[13] Information on the resources devoted to R&D is raised in the Cost Structure Census since 1999.

inputs of the Cobb-Douglas production function are included as logarithms, such zero inputs lead to missing values and result in the exclusion of the respective firm from the analysis. Moreover, zero input values are not consistent with a Cobb-Douglas production technology and would imply zero output. In order to reduce the number of reported zero input quantities we aggregated the inputs into the following categories: material inputs (intermediate material consumption plus commodity inputs), labor compensation (salaries and wages plus employer's social insurance contributions), energy consumption, user cost of capital (depreciation plus rents and leases), external services (e.g., repair costs and external wagework) and other inputs related to production (e.g., transportation services, consulting or marketing). All input and output series were deflated using the producer price index for the respective industry.

Table 2: Cost shares of inputs in total production

Variable	*Mean*	*Median*	*Standard deviation*	*Minimum*	*Maximum*	*Coefficient of variation*
Material inputs	0.410	0.407	0.165	0.018	0.854	40.303
Labor compensation	0.330	0.320	0.136	0.053	0.840	41.318
Energy consumption	0.021	0.013	0.023	0.001	0.170	110.663
User cost of capital	0.067	0.056	0.042	0.008	0.277	63.353
External services	0.047	0.028	0.053	0.001	0.334	112.786
Other inputs	0.092	0.079	0.059	0.010	0.362	63.601

Including the yearly depreciation values as proxy variables for capital input leads to implausibly low estimates for the output elasticity of capital. We presume that the reason for these low values is the relatively high year by year variation of depreciations. In order to reduce this volatility, we calculated average yearly depreciations by adding up for each year the depreciations in the current year and of all the preceding years that we have information about.

This sum was then divided by the number of years with observations.[14] Using this average value of yearly depreciations results in a considerably higher estimate of output elasticity of capital in the production function.

Average cost shares of these input categories and other summary statistics for the cost shares are reported in Table 2. The dominant cost categories are material inputs and payroll, which together add up to about 75 percent of expenses. All cost shares sum up to 0.967. The difference from unity of about 3.3 percent can be interpreted as the share of gross profits in production. Firms with less than 500 employees, which are only included in the Cost Structure Census as a representative random sample, have been multiplied with weights greater or equal to one for the estimation of the production function. These weights represent the relationship between the number of firms in the respective industry and size category in the full population, and the number of firms of respective size and industry that is included in our sample.[15] Since these weights are rather stable over time, we use the weights for the year 1997 for all estimations.

The sample contains a number of observations with extreme values that proved to have a considerable impact on the estimated parameters of the production function and led to implausible results. We therefore exclude those 'outliers' from the analysis for which the cost for a certain input category in relation to gross output is less than the lowest (1 percent) and the highest (99 percent) percentile. In total, these excluded cases (plus firms with zero values for certain input categories) make about 10 percent of all observations. We find that the exclusion of these extreme cases leads to considerable improvement of the estimation results.

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[14] Example: Assume that the data set provides information on depreciations of a certain firm for the years '93, '94, '95 and '96. Average yearly depreciation for the year '95 is the average of the years '93 – '95. For the year '96 it is the average of the years '93-'96 etc. For the year '93 the average equals the value for this year.

[15] Example: If only 25 percent of the firms of a particular size class are included in the sample each observation is multiplied by a factor of 4.

4. Production function estimates

In order to generate the fixed effects as a measure of technical efficiency, a Cobb-Douglas production function according to (1) was estimated on the basis of the micro-data for individual firms. Table 3 displays the parameter estimates. The second column reports the results for a pooled OLS estimation. The third column displays the results for the panel approach with fixed effects for individual firms. These serve as our measures of firms' technical efficiency.[16] In both versions we included dummy variables for the different

Table 3: Estimates for logarithmic Cobb-Douglas production function[a]

	Pooled Regression		*LSDV*	
Variable	*Estimate*	*t-value*	*Estimate*	*t-value*
Intercept	1.803**	(278.99)	fixed effects**	
Material inputs	0.373**	(645.33)	0.377**	(374.28)
Labor compensation	0.353**	(368.65)	0.412**	(212.51)
Energy consumption	0.017**	(32.93)	0.020**	(23.46)
User cost of capital	0.086 **	(110.99)	0.067**	(43.75)
External services	0.057**	(144.24)	0.046**	(108.06)
Other inputs	0.101**	(163.08)	0.070**	(94.05)
1992 dummy	0.014**	(6.52)	0.028**	(20.28)
1993 dummy	-0.005**	(-2.31)	0.008**	(5.45)
1994 dummy	-0.0003**	(-0.16)	0.012**	(8.93)
1995 dummy	0.007**	(3.28)	0.020**	(15.25)
1996 dummy	0.001	(0.56)	0.014**	(10.43)
1997 dummy	0.018**	(8.60)	0.019**	(12.82)
1998 dummy	0.018**	(8.50)	0.018**	(12.46)
1999 dummy	0.019**	(8.91)	0.019**	(16.99)
2000 dummy	0.017**	(8.16)	0.019**	(16.38)
2001 dummy	0.012**	(5.79)	0.012**	(10.89)
R^2	0.9836		0.9964	
F-test fixed effects	—		12.83**	
F-test CRS (value RS)	1332.39**	(0.9861)	21.6**	(0.9922)
Number of observations	156,053		156,053	

t-values in parentheses. *: statistically significant at the 5 percent level. **: statistically significant at the 1 percent level.

[16] Least Squares Dummy Variables method for panel data; see Baltagi (2001) and Coelli et al. (1998) for this approach.

years of the observation period, with 2002 being the year of reference. The fit of the regressions (R^2) is remarkably high and the dummies for the different years are highly significant.[17] The sum of the estimated output elasticities amounts to 0.98 for the pooled regression and to 0.99 for the panel regression.

According to neoclassical production theory profit maximizing firms will choose that combination of inputs for which the cost share of each input equals the respective elasticity of production. The relatively close correspondence of the estimated production elasticities and the average cost shares of the respective input (Table 2) indicates that the parameters of our production functions are in a plausible range and that the model is apparently properly specified. Generally, the fixed-effects panel estimates are somewhat closer to the cost shares but the differences to the results of pooled regression are rather small. The positive values of most year dummies indicate a higher productivity in the respective year than in the reference year 2002. This suggests that these dummies are not simply a measure of technical progress, because the ongoing advancement over time would lead to negative values of the year dummies. For this reason, we assume that the values of the year dummies reflect mainly the macro-economic conditions which were relatively unfavorable with a considerable underutilization of capacities in 2002 as well as in the year 1993, for which a negative value of the respective dummy variable was found.

5. The extent and distribution of technical efficiency differences across industries

We have already mentioned (Section 2) the common assumption that the distribution of technical efficiencies within an industry is skewed to the left. This means that the values of technical efficiency of most firms is clustered near the efficiency frontier and that their frequency declines with rising inefficiency. The distribution should, therefore, have a longer tail at the left

[17] Note that a Hausman-Wu test indicated correlation between fixed effects and the other explanatory variables (results are available from the authors upon request). Thus, a random effects model or a stochastic frontier framework would not be appropriate in this case.

hand side. Such a kind of skewness constitutes indeed a precondition for estimating a stochastic frontier production function (Greene, 1997). In analyses of the distribution of technical efficiency within industries we have found, however, that in 95 percent of the industries this distribution is skewed to the right (Fritsch & Stephan, 2004b). Fritsch & Stephan (2004b) explain this skewness to the right by a truncation of the efficiency distribution at low efficiency values. Such a truncation of low efficient firms occurs because these firms are not able to earn their cost and are, therefore, forced to exit the market. Since factor costs such as wages are about the same for all industries, this lower efficiency frontier should be located at about the same level of technical efficiency (for a more detailed explanation see Fritsch & Stephan, 2004b).

Figure 2 shows the distribution of technical efficiency at different relative efficiency levels across the 241 four-digit NACE industries.[18] In our analysis of cross-industry differences we compare different points of the intra-industry distribution according to the efficiency distribution curve (Figure 1). If firms in each industry are weighted with their output and sorted according to the value of the firm-specific effect in descending order, technical efficiency at the 5 percent output level is the value of the firm which represents the 5th percentile of this distribution. It is the level of technical efficiency between the most efficient 5 percent of industry output and the less efficient firms. Accordingly, technical efficiency at the 50 percent output level is the value of the median output unit and the value for the 95 percent output level is the technical efficiency at the 95th percentile, i.e. at the lower end of the efficiency scale. For each of these output levels, technical efficiency of an industry is expressed in relation to the industry with the highest value of fixed effect which is assigned a value of one. Therefore, the measure of an industries' relative level of technical efficiency can assume values between zero and unity.

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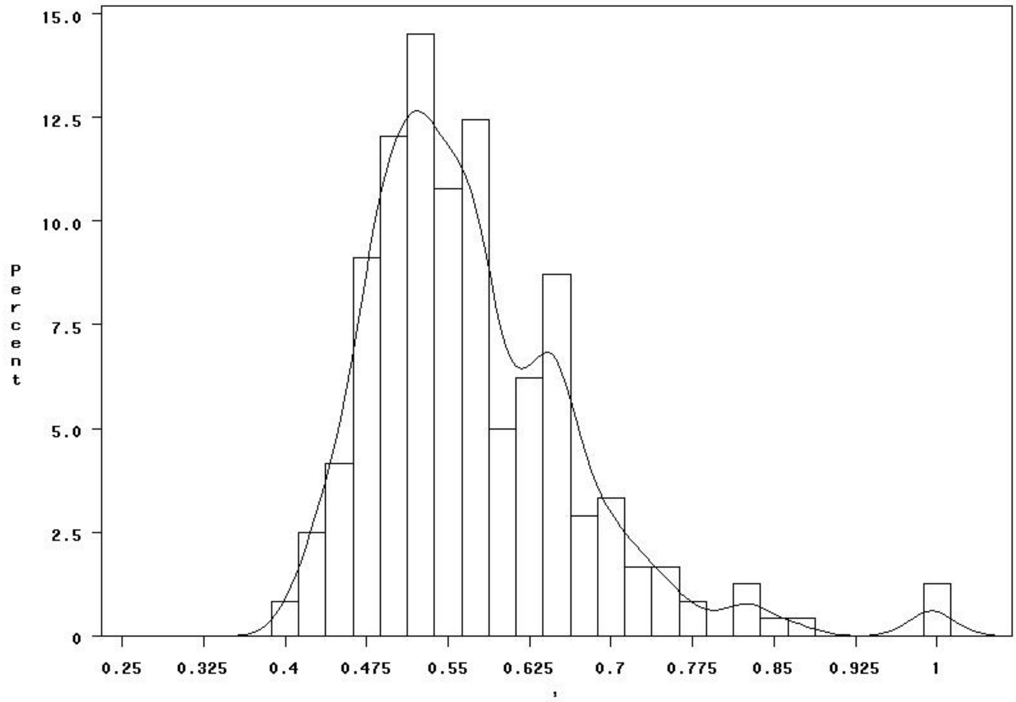
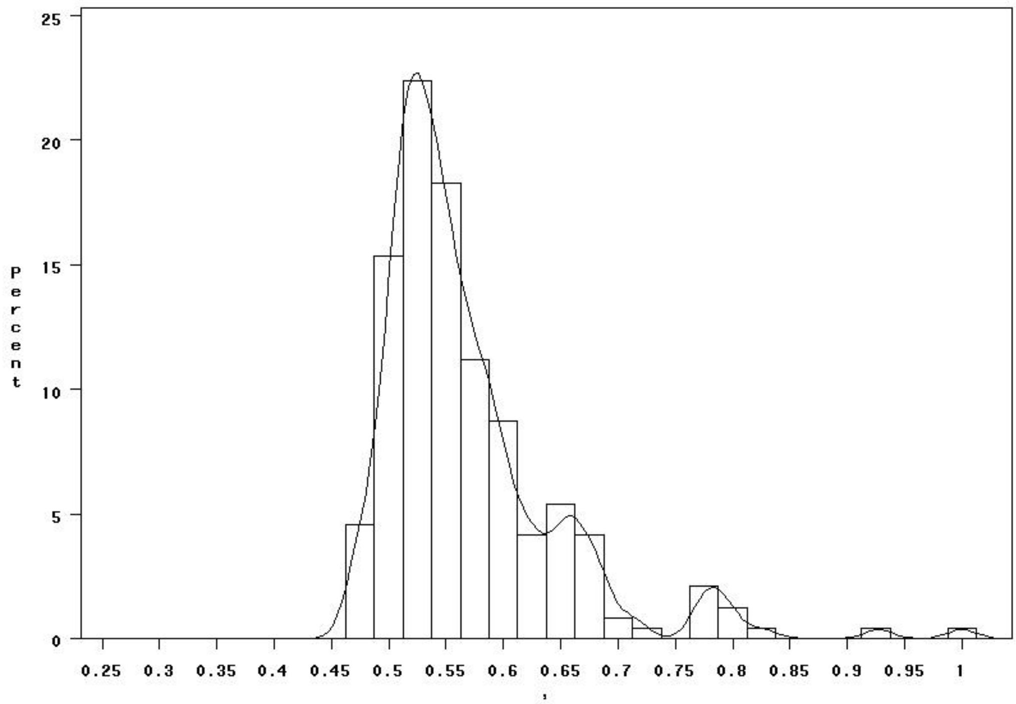
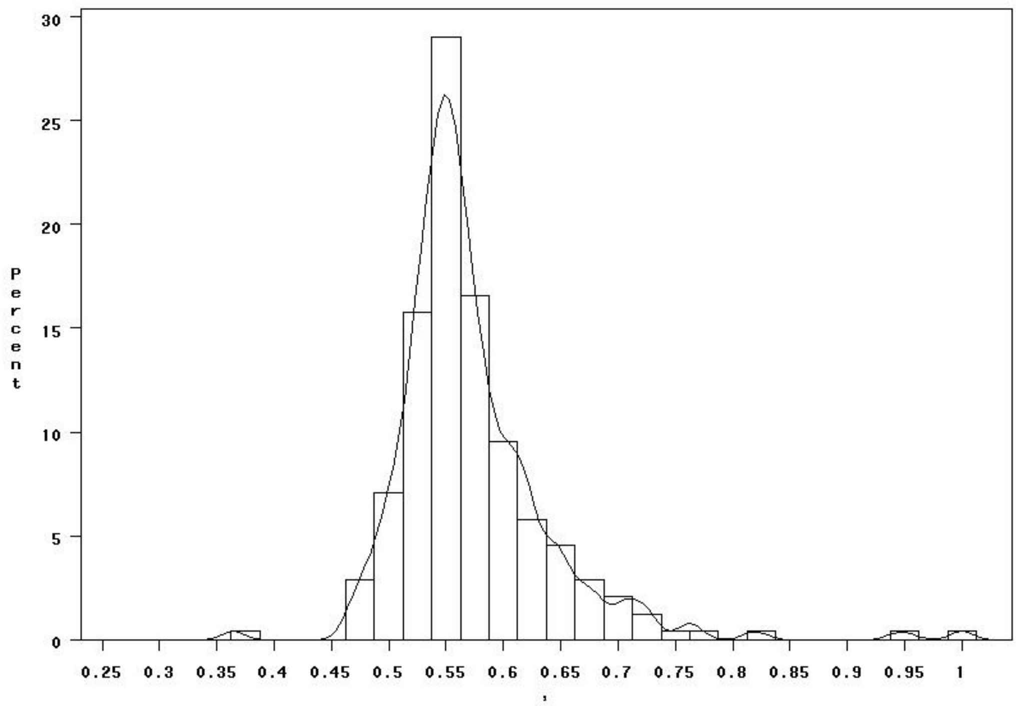
[18] Note that industries with less than five firms were excluded. We also excluded manufacture of tobacco products (NACE 16.00) because this industry is an extreme outlier with a high level of technical efficiency. This high level of technical efficiency is probably a result of the relatively high advertisement costs which are not properly taken into account in the input variables of our production function.



a) At output level 5 percent



b) At output level 50 percent



c) At output level 95 percent

Figure 2: The distribution of technical efficiency at different output levels across industries

For all output levels, we observe that the distribution of average efficiency is skewed to the right and is particularly characterized by some ‘outlier’ industries with relatively high levels of technical efficiency. Thus, the distribution of technical efficiency is positively skewed not only within industries but also across industries. The reason for this positive skewness is the truncation of the intra-industry distribution of technical efficiency at the lower end, caused by the exit of low efficient firms which do not manage to be sufficiently profitable to survive competition. Because this kind of truncation pertains to the firms at the lower end of the intra-industry efficiency distribution, the skewness of the cross-industry distribution should be less pronounced at higher intra-industry levels of efficiency. The skewness statistics for the three efficiency distributions (Table 4) are in accordance with this prediction. We observe positive values of skewness statistics indicating longer tails of the distribution at the right hand side for all three distributions. As could be expected, the value of the skewness statistic is highest for the distribution of technical efficiency at the 95 percent output level where truncation should be most significant. Another noteworthy result is that the variation of technical efficiency among industries is much larger for the firms with a relatively high level of technical efficiency (output level 5 percent) as compared to the relatively low efficient firms (95 percent output level). This is also to be expected given the truncation of the efficiency distribution at the lower end. There is a pronounced positive relationship between the relative technical efficiency of the different levels (Table 5). The correlation of relative positions across industries is relatively high. Thus, industries with a significant share of highly efficient firms are likely to also have relatively high efficient firms at the lower part of the distribution curve.

Table 4: Parameters of the distribution of technical efficiency at different output levels across industries

Statistic	TE at output level 5 %	TE at output level 50 %	TE at output level 95 %
Mean	0.572	0.569	0.572
Standard deviation	0.099	0.078	0.068
Coefficient of variation	17.23	13.65	11.94
Skewness	1.430	2.069	2.225
Kurtosis	3.383	6.138	10.082
Range	0.590	0.533	0.636
99^{th} percentile	0.990	0.826	0.820
95^{th} percentile	0.739	0.711	0.688
90^{th} percentile	0.690	0.662	0.648
Median	0.555	0.547	0.558
10^{th} percentile	0.473	0.502	0.512
5^{th} percentile	0.451	0.491	0.496
1^{st} percentile	0.420	0.471	0.470
Minimum	0.410	0.467	0.364

Table 5: Correlation of relative efficiency levels across industries†

	TE at output level 5 %	TE at output level 50 %	TE at output level 95 %
TE at output level 5 %	1	0.7183	0.4944
TE at output level 50 %		1	0.7309

† Pearson correlation coefficients. n = 241. All reported correlations are statistically significant at the 1 percent level.

Table 6: Average level and distribution of technical efficiency in two-digit industries†

Industry [NACE code]	Number of firms	Technical efficiency at output level 5 %	50 %	95 %	h-area
Mining of coal; extraction of peat [10]	67	0.734	0.612	0.603	0.122
Other mining and quarrying [14]	301	0.914	1.000	0.828	0.188
Food and beverages [15]	3,965	0.905	0.864	0.814	0.111
Textiles [17]	1,405	0.821	0.681	0.674	0.122
Apparel, fur [18]	914	0.909	0.795	0.782	0.159
Leather; luggage, saddlery, footwear [19]	361	0.850	0.721	0.740	0.200
Wood and cork (except furniture) [20]	1,193	0.860	0.673	0.688	0.129
Pulp and paper [21]	934	0.864	0.692	0.701	0.122
Publishing, printing, reproduction [22]	1,691	0.848	0.823	0.716	0.119
Coke, refined petroleum products and nuclear fuel [23]	57	1.000	0.936	1.000	0.176
Chemicals [24]	1,500	0.832	0.720	0.720	0.095
Rubber and plastics [25]	2,020	0.830	0.644	0.680	0.111
Other non-metallic mineral products [26]	2,120	0.856	0.694	0.706	0.121
Basic metals [27]	1,020	0.851	0.773	0.698	0.131
Fabricated metal products (except machinery and equipment) [28]	4,732	0.845	0.674	0.680	0.092
Machinery and equipment [29]	5,251	0.816	0.628	0.666	0.080
Office machinery and computers [30]	199	0.834	0.675	0.704	0.180
Electrical machinery [31]	1,740	0.832	0.611	0.655	0.066
Radio, television and communication equipment [32]	486	0.808	0.768	0.743	0.149
Medical, precision and optical instruments [33]	1,500	0.820	0.679	0.671	0.099
Motor vehicles, trailers and semi-trailers [34]	1,251	0.885	0.642	0.728	0.069
Other transport equipment [35]	372	0.775	0.588	0.667	0.105
Furniture; manufacturing n.e.c. [36]	2,103	0.835	0.677	0.667	0.074
Recycling [37]	96	0.968	0.791	0.863	0.199

† The two-digit industries NACE 11, 12 are excluded because of an insufficient number of observations. NACE 16 (tobacco) is excluded because of extreme values.

Table 6 exhibits average technical efficiencies for the two-digit industries at different output levels. It also gives the number of firms at this 2-digit level. Furthermore, the corresponding within-industry heterogeneity of technical efficiency is reported, as indicated by the h-area measure. At the 2-digit level, the differences of technical efficiency across industries are less pronounced than at the 4-digit level. Again, variation is much higher at the 5 percent output level (i.e. among the firms with relatively high levels of technical efficiency) as compared to the 95 percent level (the relatively inefficient firms). Relatively large levels of within-industry heterogeneity of technical efficiency can be found for the leather industry (NACE 19) as well as for the recycling industry (NACE 37) whereas, for instance, the automobile industry (NACE 34) is quite homogenous in this respect.

6. Hypotheses and variables

Differences of technical efficiency across industries may have a number of explanations.[19] One can expect that factor inputs such as tangible and intangible capital will have a strong impact on the level of technical efficiency. Regarding *physical capital intensity,* a comprehensive equipment of the workforce with capital goods may indicate a broad application of available technology that can lead to highly efficient production. We therefore expect a positive impact of high capital intensity on technical efficiency. Our measure for capital intensity is a firms' average yearly depreciation over gross production. Furthermore, the effect of high *human capital intensity*, i.e. the share of skilled labor that is used in the production process, on technical efficiency is expected to be positive. We use the share of employees with a university degree as the indicator for the knowledge intensity. One may expect that a high *intensity of Research and Development (R&D)* in an industry has a positive effect on average efficiency. This may particularly hold for process innovation activity that is directly aimed at improving productivity. However, Albach (1980) and Caves & Barton (1990) found a negative impact of R&D

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[19] See Caves (1992) for a review of hypotheses and the empirical evidence.

intensity on technical efficiency. In explaining this negative effect Caves & Barton (1990, 76) suppose that R&D expenditures made in a certain industry are only a poor predictor of the innovativeness of that industry because large parts of the innovation output is applied in other industries. We measure the intensity of innovation activity with the average yearly share of R&D expenditure in the years 1999-2002 on gross production (source: Cost Structure Census).

Market structure and competition should also have a considerable effect on the level of an industry's technical efficiency. If competition is intense, firms with slack in the utilization of inputs are not sufficiently profitable and will sooner or later have to exit the market. One main aspect of competition is market contestability. A high *start-up rate* in an industry indicates a high level of contestability implying strong competitive pressure. We may, therefore, expect a positive relationship between the level of start-ups and average technical efficiency. The start-up rate is calculated here as the average yearly number of newly founded businesses in the period 1998-2001 over the average number of employees in the respective industry.[20] According to the presumption that competition stimulates firms' technical efficiencies, we also expect an increase of technical efficiency as *market concentration* decreases. One may, however, also argue that an 'atomistic' market structure with a high number of small suppliers is characterized by a relatively low level of competitive pressure and that, under such circumstances, an increase of concentration may lead to some intensification of this competitive pressure. Such a stimulating effect of concentration on the intensity of competition and efficiency may occur until a certain concentration level is reached, from which point on increased market power leads to reduction of competitive pressure and allows for inefficiencies. Therefore, the relationship between market structure, as measured by the Herfindahl index, and the average level of inefficiency of an industry could be u-shaped. The Herfindahl index has been calculated on the

[20] The data are taken from the establishment file of the German Social Insurance Statistics; see Fritsch & Brixy (2004) for a description of this data source.

basis of the Cost Structure Census. A measure of the competitive pressure that is created by international competition is the *ratio of imports* to domestic production. The higher the import quota the more intense the competition of foreign suppliers, inducing a relatively high level of technical efficiency in the surviving firms.

Table 7: Overview of hypotheses about the effects of different factors on the average level of efficiency across industries

Determinants of technical efficiency	*Expected sign for relationship with technical efficiency*
Tangible and intangible capital	
Physical capital intensity	+
Human capital intensity	+
R&D intensity	– / +
Market structure and competition	
New firm formation rate	+
Market concentration	– / +
Import share	+
Production technology	
Average firm size	– / +
Vertical specialization	+
Further industry characteristics	
Entrepreneurial character of an industries' technological regime	+
Output growth rate	– / +

Another group of factors that may affect the level of technical efficiency in an industry consists of production technology (e.g. the extent of economies of scale) and the degree of vertical specialization. The degree of *vertical specialization* in an industry can be measured, for example, as the ratio of intermediate inputs to internal wage cost. This measure reflects the degree of labor division and outsourcing in an industry. A relatively high ratio of intermediate inputs to internal wage cost indicates a high level of outsourcing and division of labor. Since labor division and specialization can be assumed to be conducive to technical efficiency the relationship should be positive. If large firm size allows for the realization of cost advantages, the relationship between an industry's *average firm size*[21] and the level of technical efficiency should be positive (Caves & Barton, 1990, 82-84). There are, however, at least two reasons for expecting a negative relationship. First, large firms may, because of their size, suffer more from bureaucratic frictions and lacking motivation of personnel than smaller firms. And second, if small firms run into economic problems due to a low technical efficiency, they are much more likely to exit the market than larger firms.[22] Due to this effect of market selection, the surviving small firms that we observe may on average show a higher level of technical efficiency than the larger firms.

Two further industry characteristics may also have significant effect on the level of technical efficiency: the characteristics of an industry's technological regime and its output growth rate. An industry under a routinized *technological regime* can be expected to be rather homogeneous due to intensive price competition among large suppliers of rather similar goods that are manufactured with highly standardized processes (Audretsch, 1995, 39-64; Winter, 1984). For this reason and due to a relatively high share of R&D that is devoted to process innovation in such a regime, the average technical efficiency level of the industry should be relatively high. Under an entrepreneurial regime, products and processes are more diverse inducing a relatively high importance of competition by quality as compared to price competition. Moreover, processes are less standardized. This high level of heterogeneity can be expected to result in an average level of efficiency that is relatively low.

The development stage or maturity of an industry is reflected by the average of firms' growth rates. However, the effect of the *industry's growth rate* on the average technical efficiency level is unclear. On the one hand,

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[21] Measured as mean of the log(number of employees); source: Cost Structure Census.

[22] Large firms are much more able to shrink as a reaction to economic problems than smaller firms which have a higher risk of falling below the minimum efficient size when reducing output.

growth may induce high investment and speedy adoption of new technology. On the other hand, economic prosperity may be associated with only low pressure to modernize machinery and, thus, allows for relatively low efficiency and a correspondingly high degree of heterogeneity. We include other industry characteristics such as the share of West German firms and the type of produced good (intermediate, investment goods, durable and non-durable consumer goods) as control variables in the regression. An overview on our hypotheses is given in Table 7. Table A1 in the Appendix gives the definition of the independent variables as used in the empirical analysis. Table A2 provides descriptive statistics of the independent variables and Table A3 gives the correlations and tolerance factors of all right-hand side variables. The values for the tolerance factor indicate that multicollinearity between the explanatory variables is not significant.[23]

7. Econometric results

For analyzing the determinants of technical efficiency across industries, regressions based on three different methods were estimated. The first method was ordinary least squares (OLS). Since OLS is rather sensitive with regard to extreme values, we also applied Reweighted Least Squares (RLS) to test whether the results are robust with regard to such extreme observations. RLS is based on Least Trimmed Squares (LTS) regression results (see Rousseeuw & Leroy, 1987, for details). As a third method we performed regressions based on the rank values of the variables (Conover & Iman, 1982; Iman & Conover, 1979; Table 8). This approach may have two advantages. First, like LTS regression, rank regression is rather robust with regard to outliers. Secondly, because values are rank transformed, non-linear monotonous relationships may be identified that would not have been found with the other two regression methods. However, as far as ‘true’ relationships are linear, rank regression will

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[23] As suggested by Besley et al. (1980), the critical value for the tolerance indicating severe multicollinearity is 0.1 or below. For all variables, tolerances are well above 0.1. That multicollinearity is negligible for the chosen specifications is also confirmed by the condition indices for the regressions, which are all well below the critical value of 100.

Table 8: Estimations on the determinants of differences in technical efficiency at the 5 percent output level across industries†

	OLS		RLS		Rank	
	Estimate	t-value	Estimate	t-value	Estimate	t-value
Intercept	0.530**	(7.70)	0.443**	(9.70)	98.1	(1.75)
Vertical specialization	0.029**	(6.32)	0.032**	(10.62)	0.378**	(5.47)
Capital intensity	1.838**	(5.54)	0.953**	(3.72)	0.159*	(2.23)
Human capital intensity	0.506**	(4.96)	0.058	(0.71)	0.356**	(4.55)
R&D intensity	-0.615	-(0.77)	0.883	(1.60)	-0.138	-(1.86)
Average firm size	-0.028**	-(3.36)	-0.009	-(1.67)	-0.254**	-(3.18)
New firm formation	4.128*	(2.20)	4.750**	(3.80)	0.139	(1.91)
Herfindahl index	-0.139**	-(2.63)	-0.173**	-(4.84)	-0.167*	-(2.47)
Average sales growth	-0.430**	-(2.91)	-0.151	-(1.46)	-0.054	-(0.87)
Share of West German Firms	0.030	(0.57)	0.048	(1.40)	-0.019	-(0.32)
Dummy for intermediate products	-0.006	-(0.28)	0.000	-(0.02)	-0.076	-(0.52)
Dummy for producers of investment goods	-0.037	-(1.47)	-0.014	-(0.85)	-0.318*	-(2.00)
Dummy for producers of non-durable consumer goods	0.027	(1.14)	0.029	(1.86)	0.182	(1.23)
R-squared (adj.)	0.392		0.503		0.327	
Error degrees of freedom	228		201		228	
Root mean squared error	0.079		0.05		58.7	
Number of observations	241		214		241	

† t-values in parentheses. *: statistically significant at the 5 percent level. **: statistically significant at the 1 percent level. For all reported regressions, specification tests according to White (1980, p. 822) do not reject the null hypothesis that the errors are homoscedastic and independent of the regressors. These test results are available from the authors upon request.

be relatively inefficient. The dependent variables of the regressions are technical efficiencies at the 5, 50 and 95 percent output level of industries. The estimation results are shown in Tables 8 to 10. Table 11 gives an overview on the results.

Regarding the importance of tangible and intangible capital intensity for average technical efficiency, we find a significant positive impact from both physical and human capital intensity. The relationship between an industry's R&D intensity and its technical efficiency is not statistically significant for average technical efficiency the 5 and 50 percent output level. This is in line with the descriptive evidence of Table 6, which indicates that R&D intensive

Table 9: Estimations on the determinants of differences in technical efficiency at the 50 percent output level across industries†

	OLS		RLS		Rank	
	Estimate	t-value	Estimate	t-value	Estimate	t-value
Intercept	0.448**	(10.22)	0.434**	(18.07)	-25.5	-(0.52)
Vertical specialization	0.039**	(13.38)	0.037**	(22.54)	0.505**	(8.42)
Capital intensity	1.429**	(6.75)	0.912**	(6.03)	0.188**	(3.02)
Human Capital Intensity	0.249**	(3.84)	0.078	(1.71)	0.350**	(5.14)
R&D intensity	-0.029	-(0.06)	0.663*	(2.22)	-0.199**	-(3.08)
Average firm size	-0.023**	-(4.47)	-0.012**	-(4.02)	-0.216**	-(3.11)
New firm formation	2.610*	(2.18)	3.928**	(6.09)	0.149*	(2.36)
Herfindahl index	0.086**	(2.54)	0.056**	(2.84)	0.118*	(2.02)
Average sales growth	-0.134	-(1.43)	0.106*	(2.01)	-0.003	-(0.05)
Share of West German Firms	0.069*	(2.10)	0.041*	(2.20)	0.081	(1.55)
Dummy for intermediate products	-0.002	-(0.11)	-0.007	-(0.89)	-0.009	-(0.07)
Dummy for producers of investment goods	-0.001	-(0.05)	0.001	(0.12)	-0.101	-(0.73)
Dummy for producers of non-durable consumer goods	0.037*	(2.48)	0.021**	(2.64)	0.347**	(2.69)
R-squared (adj.)	0.601		0.801		0.492	
Error degrees of freedom	228		192		228	
Root mean squared error	0.05		0.025		50.9	
Number of observations	241		205		241	

† t-values in parentheses. *: statistically significant at the 5 percent level. **: statistically significant at the 1 percent level. For all reported regressions, specification tests according to White (1980, p. 822) do not reject the null hypothesis that the errors are homoscedastic and independent of the regressors. These test results are available from the authors upon request.

industries – e.g. chemicals [NACE 24], office machinery and computers [NACE 30] or radio, television and communication equipment [NACE 32] – are not among the most efficient industries. However, the relationship between R&D and efficiency is strongly negative for the 95 percent output level, i.e. for the least efficient firms in the industries. This confirms the findings of Albach (1980) and Caves & Barton (1990). As already mentioned, this result could be explained by the conjecture that a considerable part of the innovations generated in an industry have no effect on this industry's performance because they are mainly applied in other industries. Another explanation could be that the efficiency enhancing effect of R&D expenditure occurs with a considerable

Table 10: Estimations on the determinants of differences in technical efficiency at the 95 percent output level across industries[†]

	OLS		RLS		Rank	
	Estimate	t-value	Estimate	t-value	Estimate	t-value
Intercept	0.430**	(11.38)	0.579**	(22.99)	-49.0	-(0.98)
Vertical specialization	0.030**	(11.97)	0.019**	(10.65)	0.380**	(6.20)
Capital intensity	1.255**	(6.87)	0.650**	(5.53)	0.119	(1.87)
Human Capital Intensity	0.251**	(4.48)	0.284**	(8.09)	0.289**	(4.16)
R&D intensity	-1.783**	-(4.08)	-2.068**	-(7.77)	-0.259**	-(3.94)
Average firm size	-0.008	-(1.67)	-0.019**	-(6.42)	-0.097	-(1.38)
New firm formation	0.057	(0.06)	-0.983	-(1.67)	0.118	(1.82)
Herfindahl index	0.151**	(5.19)	0.099**	(5.51)	0.202**	(3.38)
Average sales growth	0.089	(1.09)	0.168**	(3.44)	0.126*	(2.30)
Share of West German Firms	0.046	(1.60)	0.006	(0.33)	-0.029	-(0.54)
Dummy for intermediate products	-0.009	-(0.73)	-0.014	-(1.87)	0.146	(1.13)
Dummy for producers of investment goods	-0.002	-(0.15)	-0.018*	-(2.26)	-0.040	-(0.28)
Dummy for producers of non-durable consumer goods	0.023	(1.77)	0.013	(1.71)	0.450**	(3.42)
R-squared (adj.)	0.617		0.695		0.471	
Error degrees of freedom	228		193		228	
Root mean squared error	0.043		0.023		52.041	
Number of observations	241		206		241	

† t-values in parentheses. *: statistically significant at the 5 percent level. **: statistically significant at the 1 percent level. For all reported regressions, specification tests according to White (1980, p. 822) do not reject the null hypothesis that the errors are homoscedastic and independent of the regressors. These test results are available from the authors upon request.

time lag. The negative sign of the coefficient would also be consistent with the assumption that the least efficient firms make relatively high R&D expenditures in order to compensate for their inefficiency.

The impact of industry concentration as measured by the Herfindahl index on technical efficiency is negative for the most efficient firms at output level 5 percent, but positive for output levels 50 percent and 95 percent. The highest level of significance is found for the 95 percent output level. These findings suggest that for the most efficient firms, high market concentration leads to a relatively low level of average technical efficiency because competitive pressure for these firms in concentrated markets is low. However, at the lower part of the efficiency distribution curve, competitive pressure and thus efficiency in concentrated markets seems to be quite intense**.** The results with regards to another source of competitive pressure, the occurrence of new firm entry into the industry, are completely in line with our expectations. A high level of new firm formation leads to a high level of average efficiency, particularly among the relatively efficient firms at output level 5 percent and 50 percent. This suggests a stimulating role of market contestability and competition on technical efficiency. No statistically significant effect could be found for the import share of an industry. Therefore, this variable has not been included in the final version of the empirical models that are presented here.

Table 11: Summary of findings†

	Technical efficiency at different output levels		
Independent variables	5 %	50 %	95 %
Tangible and intangible capital			
Physical capital intensity	+	+	+
Human Capital Intensity	+	+	+
R&D intensity	n.s.	(+ / –)	–
Market structure and competition			
New firm formation rate	+	+	n.s.
Herfindahl index	–	+	+
Import share	n.s.	n.s.	n.s.
Production technology			
Average firm size	–	–	(–)
Vertical specialization	+	+	+
Industry characteristics			
Average of firms' sales growth	(–)	+	+
Share of West German firms	n.s.	+	n.s.
Entrepreneurial regime	n.s.	n.s.	n.s.
Dummy for intermediate products	n.s.	n.s.	(–)
Dummy for producers of investment goods	(–)	n.s.	(–)
Dummy for producers of non-durable consumer goods	n.s.	+	(+)

† Signs of coefficient if statistically significant. Without parentheses: sign statistically significant at the 5 percent level in at least two models; in parentheses: variable was statistically significant at the 5 percent level in only one of the models reported; n.s.: variable was not statistically significant at the 5 percent level in any of the models reported.

One of the strongest impacts on average technical efficiency is exerted by the degree of vertical specialization and labor division in an industry. Thus, as has been shown in other studies (Görzig & Stephan, 2002), a high degree of vertical disintegration leads to a high level of technical efficiency. It is quite remarkable that the effect of an industry's average firm size on technical efficiency is significantly negative, particularly at the upper (5 percent output level) and middle part (50 percent output level) of the efficiency distribution curve. The negative relationship indicates that larger firms tend to suffer from higher levels of technical inefficiency than smaller firms. This finding could be explained by higher complexity in larger firms that makes identification of inefficiency more difficult than in small firms. Another explanation is based on a 'survivor bias' in the data: larger firms are better able to survive high levels of technical inefficiency than small firms which may be more likely forced to exit if they are inefficient. In this case, however, we would expect a relatively pronounced negative relationship between average size and efficiency even for the low efficient firms, i.e. at the 95 percent level.

High average sales growth rate in an industry is conducive for attaining a high average efficiency level at the 50 percent and 95 percent output level, i.e. for the average and low efficient firms. It is somewhat surprising that industries with a larger share of West German firms are not generally more efficient, but only at output level 50 percent. Our estimates suggest that industries producing durable consumer goods are more efficient than those producing non-durable goods. Industries for intermediate goods and for investment goods tend to attain a relatively low level of technical efficiency. No significant effect could be found for the technological regime of an industry. This variable has, therefore, been omitted in the final version of the model due to close correlation with average firm size.

8. Summary and Conclusions

In this paper we have estimated technical efficiencies of firms as fixed effects. Our analysis is based on a unique and representative panel data set of about 35,000 firms from the German Cost Structure census. The fixed effects approach has two major advantages over the stochastic frontier framework which has been applied in most of the previous studies. First, the fixed effects approach does not require that a firm's technical efficiency and its factor inputs are uncorrelated. For our sample we can show that a significant degree of correlation between these variables and technical efficiency estimates exists. Second, the fixed effects approach does not require the assumption that the distribution of technical efficiencies is negatively skewed. Indeed, we find pronounced positive skewness of the efficiency distribution within as well as across industries. The explanation for this finding is a truncation at the lower efficiency end. The least efficient firms are not able to earn their cost and, therefore, are forced to exit the market.

Our empirical analyses have shown that there are considerable differences of average technical efficiency across industries. We identified a number of factors that are important for explaining these differences. The strongest effect was found for the degree of vertical specialization, i.e. a high degree of labor division between firms (outsourcing) results in relatively high levels of average efficiency. Furthermore, physical as well as human capital intensity has a positive impact on average technical efficiency. Surprisingly, high R&D expenditures are not conducive for the efficiency of an industry. In fact, we find a negative sign for the impact of R&D intensity on technical efficiency for the least efficient firms. This finding may be explained by a pronounced diffusion of innovations across industries or by a long time lag for R&D expenditure to become effective. One may also assume that the least efficient firms have higher R&D expenditures to compensate for their inefficiency.

The positive effect that we find for the new firm formation rate indicates that competition and contestability are stimulating for technical efficiency. Average efficiency is higher in high-entry industries because survival of inefficient firms is threatened by intensive competition. This indicates that slack and sub-optimal use of factor inputs can only persist when competition is not very pronounced.

Our analyses have so far been static as they regarded only the time-invariant level of technical efficiency thereby neglecting its dynamic evolution and the consequences for competition and industry evolution. As soon as better data becomes available, i.e. longer series of firm-level data, future research should investigate these dynamics of technical efficiency.

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Appendix

Table A1: Definition of independent variables

Variable	*Definition*
Capital intensity	Mean of annual depreciations plus expenditures for rents and leases over sales at firm-level from 1992 to 2002.
Human capital intensity	Number of employees with a university degree divided by number of untrained employees in the industry.
R&D intensity	Mean of R&D over gross production in the 1999 to 2002 period in the industry.
New firm formation rate	Mean annual number of new firms[a] per employee[b] at the 4-digit industry level 1998-2001.
Herfindahl index	Mean of Herfindahl index over the 1992 to 2002 period
Import share	Ratio of imports[c] to domestic production, average of 1992 to 2002 period.
Average firm size	Log of mean number of employees in respective industry from 1992 to 2002.
Vertical specialization	Ratio of intermediate products to internal wage costs, average of 1992 to 2002 period.
Entrepreneurial character of industry	Share of R&D expenditure on gross production in firms with less than 50 employees over share of R&D expenditure in firms of all size categories. Mean value of the 1999-2002 period.
Average sales growth	Average of annual firms' growth rate of sales in the industry, mean of period 1992-2002.
Share of West German firms	Proportion of firms with headquarter in West Germany.
Producer type	Intermediate products, investment good, durable consumer goods, non-durable consumer goods.

Table A2: Descriptive Statistics

	Mean	Std Dev	Median	Minimum	Maximum
Vertical specialization	2.035	1.276	1.710	0.289	9.034
Capital intensity	0.045	0.018	0.040	0.012	0.143
Human Capital Intensity	0.079	0.068	0.054	0.003	0.477
R&D intensity	0.007	0.009	0.003	0.000	0.049
Average firm size	5.208	0.795	5.122	3.711	9.268
New firm formation	0.002	0.003	0.001	0.000	0.022
Herfindahl index	0.100	0.112	0.055	0.002	0.547
Average sales growth	0.020	0.038	0.019	-0.095	0.150
Share of West German Firms	86.73	10.54	89.47	33.33	100.00
Dummy intermediate products	0.548	0.499	1.000	0.000	1.000
Dummy investment goods	0.158	0.365	0.000	0.000	1.000
Dummy non-durable consumer goods	0.232	0.423	0.000	0.000	1.000

Table A3: Tolerance factors (Tol) and correlations between independent variables[*]

	Tol	TE output 50 %	Capital intensity	Human Capital Intensity	R&D intensity	Vertical specializa-tion	Average firm size	Herfindahl index	New firm formation	Average sales growth	Share of West German Firms	Dummy interme-diate products	Dummy investment goods	Dummy non-durable consumer
TE output 50 %	—	—	0.186**	0.048	-0.164*	0.595**	-0.164*	0.222**	0.086	-0.101	-0.048	-0.040	-0.248**	0.327**
Capital intensity	0.707	0.035	—	0.004	-0.157*	-0.149	0.069	0.188**	-0.055	0.048	-0.113	0.432**	-0.255	-0.193**
Human Capital Intensity	0.535	0.003	0.048	—	0.619**	-0.082	0.366**	0.178**	-0.159*	0.234**	0.086	-0.107	0.360	-0.139
R&D intensity	0.496	-0.293**	-0.108	0.569**	—	-0.154*	0.372	0.085	-0.101	0.306**	0.116	-0.086	0.352	-0.226**
Vertical specialization	0.763	0.494**	-0.213**	-0.050	-0.113	—	0.046	0.167**	-0.178**	0.023	-0.201**	-0.029	-0.204	0.248**
Average firm size	0.608	-0.156*	0.094	0.535**	0.457**	0.102	—	0.317**	-0.438**	0.175*	-0.115	0.023	0.157	-0.125
Herfindahl index	0.732	0.261**	0.122	0.275**	0.071	0.312**	0.324**	—	-0.034	-0.048	-0.252**	0.166**	-0.141	-0.048
New firm formation	0.727	0.060	-0.200**	-0.342**	-0.244**	-0.241**	-0.587**	-0.246**	—	-0.166*	0.104	-0.096	-0.093	0.114
Average sales growth	0.821	-0.101	0.120	0.276**	0.324**	0.036	0.260**	-0.094	-0.258**	—	0.006	0.167**	0.087	-0.242**
Share of West German Firms	0.868	-0.072	-0.087	0.018	0.037	-0.281**	-0.170**	-0.298**	0.086	0.025	—	-0.046	0.088	-0.004
Dummy interme-diate products	0.201	-0.026	0.515**	-0.002	-0.079	0.015	0.008	0.149*	-0.196**	0.162*	-0.012	—	-0.476	-0.605**
Dummy investment goods	0.306	-0.302**	-0.307**	0.358**	0.359**	-0.241**	0.173**	-0.191**	0.003	0.097	0.049	-0.476**	—	-0.238**
Dummy non-dura-ble consumer goods	0.257	0.352**	-0.223**	-0.242**	-0.271**	0.208**	-0.119	0.000	0.138*	-0.238**	-0.020	-0.605**	-0.238**	—

[*] Braivais-Pearson correlation coefficients above, Spearman correlation coefficients below the diagonal. *: statistically significant at the 5 percent level. **: statistically significant at the 1 percent level.

Note: Tol is defined as (1-Rsquare) of a regression of the respective variable on the other independent variables.