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What Determines the Technical Efficiency of a Firm? The Importance of Industry, Location, and Size*

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Abstract

This paper investigates the factors that explain the level of technical efficiency of a firm. In our empirical analysis, we use a unique sample of about 35,000 firms in 256 industries from the German Cost Structure Census over the years 1992-2004. We estimate the technical efficiency of the firms and relate it to firm- and industry-specific characteristics. One third of the explanatory power is due to industry effects. Size accounts for another 25 percent and the headquarters' location explains ten percent of the variation in efficiency. Most other firm characteristics such as ownership structure, legal form, age of the firm and outsourcing activities have an extremely small explanatory power. R&D activity does not exert any positive influence on technical efficiency.

Keywords: Frontier analysis, determinants of technical efficiency, firm performance, industry effects, regional effects.

JEL Classification: D24, L10, L25

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1. Introduction

The classical microeconomic textbook considers firms to be homogeneous units. Accordingly, all firms are assumed to operate at the same level of productivity or technical efficiency.[1] However, empirical studies frequently showed that in the real world some firms are more efficient than others (Caves 1989). While some firms operate at the technological frontier and potentially earn high profits, others lag considerably behind and are barely able to survive. This paper analyzes the determinants of technical efficiency at the firm-level. What are the reasons for diverging efficiency of firms? Which factors can explain the fact that some firms are more efficient than others?

Our econometric analysis is based on the Cost Structure Census of the German Federal Statistical Office. This is a unique and representative micro-panel data set covering about 35,000 firms over the period of 1992 to 2004. The Cost Structure Census enables us to investigate the relative importance of a broad range of determinants of efficiency, which has not been investigated in previous studies due to data constraints. Unlike most studies, we estimate technical efficiencies as firm-specific fixed effects as proposed by Schmidt and Sickles (1984). One main advantage to this approach is that it does not involve any a priori assumption regarding the distribution of technical efficiency across firms as is required in the stochastic frontier framework. Such distributional assumptions may be regarded as being quite restrictive and are possibly not supported by the data.

The structure of the remaining paper is as follows. Section 2 reviews the results of previous studies of the determinants of efficiency followed by a discussion of methodology (section 3). Section 4 describes the data in some detail. The results of the empirical analysis are presented in section 5. Section 6 concludes.

[1] A firm is said to be technically efficient if it derives the maximum output from a given bundle of inputs within given technology, i.e., if it attains the highest possible productivity. The concept of technical efficiency was introduced by Farrell (1957), who used the concept of efficiency proposed by Koopmans (1951) and the radial type of efficiency measure considered by Debreu (1951).

2. Determinants of efficiency – previous findings

It is highly plausible to expect that a high level of competition will enhance the efficiency of firms (see Lovell 1993). Accordingly, Carlsson (1972) arrived at the conclusion that the technical efficiency of Swedish industries suffers from various protections against competition; Bloch (1974) found the same to be true for Canada. Caves and Barton (1990) conducted studies in the USA and showed that more intensive competition leads to more efficient technical choices. Based on an analysis of firms from 19 UK manufacturing sectors, Hay and Liu (1997) conclude that in a more competitive market environment firms have a relatively strong incentive to improve their efficiency. Accordingly, many studies find that industry affiliation of a firm which can be regarded as a proxy of the competitiveness of the market environment explains a large portion of the differences in the firms' performances (e.g., Schmalensee 1985; Wernerfelt and Montgomery 1988). Beeson and Husted (1989) in a cross-state study for the US found that a considerable part of the variation of efficiency can be attributed to regional differences of the labor force characteristics, levels of urbanization and industrial structure. An illustrative example for the role of regional determinants of efficiency is the prevailing difference of productivity between East and West Germany.[2]

With regard to the determinants that are internal to a firm, Alvarez and Crespi (2003) in an analysis of micro-, small-, and medium-sized Chilean manufacturing firms (1,091 firms from all manufacturing industries in 1996) found that efficiency is positively associated with the experience of the workers, modernization of physical capital and product innovation activity. Other variables such as outward orientation, education level of the owner and participation in public support programs did not affect the efficiency of

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[2] E.g., Barrell and te Velde (2000), Czarnitzki (2005), Funke and Rahn (2002), Funke and Strulik (2000) Many of the existing empirical analyses of regional differences of productivity and efficiency are more or less based on case studies for selected industries and regions, and they do not apply a production function framework. Studies using more comprehensive data sets and applying sophisticated econometric methods include the regional dimension only in a rather rudimentary way. For example, the comparisons between East and West Germany (e.g., Funke and Rahn 2002; Mallock 2005) do not account for the large differences of location conditions within the two parts of the country, e.g., between rural areas in the northern part and the industrialized city regions of Dresden and Jena in the southern regions of East Germany (Saxony, Thuringia).

the firms. Gumbau-Albert and Maudos (2002), using a complete panel of 1,149 Spanish firms from 18 manufacturing sectors, arrived at the conclusion that firm size and the amount of investment into physical assets is conducive to technical efficiency. Efficiency was also relatively high in firms that were subject to high competitive pressure on the market. In this study, the lowest levels of efficiency were found in the firms operating in more concentrated markets with a presumably low level of competition and in firms with public ownership participation. Torii (1992) claimed that the efficiency can be related to the scale or size of a firm if it is assumed that maintaining or improving efficiency demands a cost in terms of the firm's management. A number of studies found that a high level of outsourcing has a positive effect on efficiency, but some studies also state that the positive role of outsourcing is overestimated (see Heshmati 2003). The evidence of the effect of a firm's ownership structure and legal form on efficiency is mixed (e.g., Shleifer 1998). One stream of literature states that it has a considerable influence on a firm's technical efficiency (e.g., Bottasso and Sembenelli 2004) while others state that it is unimportant (e.g., Orazem and Vodopivec 2003).

3. Methodology for measuring technical efficiency

A point of reference is required that can be used to measure the efficiency level of the unit under inspection for the assessment of the technical efficiency of a firm.[3] The stochastic frontier model as proposed simultaneously by Aigner*, et al.* (1977) and Meeusen and Broeck (1977) is the most commonly used approach for measuring technical efficiency. The stochastic frontier model of Battese and Coelli (1995) can be applied if panel data is available. Though the stochastic frontier models have some virtue in distinguishing efficiency from other random influences on a firm's output, they are, however, based on rather restrictive assumptions. Firstly, a distributional assumption on the inefficiency term is imposed which might not be supported by the data. For instance, Schmidt and Lin (1984) showed that if the skewness of residuals resulting from an ordinary least squares

[3] See Mayes*, et al.* (1995) and Kumbhakar and Lovell (2000) for an overview of different approaches for assessing the efficiency of firms.

(OLS) regression is positive, the stochastic frontier approach should not be applied.[4] Secondly, it is assumed that technical efficiency and production inputs are not correlated. In empirical applications, however, such a correlation is rather likely to exist, resulting in inconsistent parameter estimates. Thirdly, the conditional mean model of Battese and Coelli (1995) can only be estimated with a moderate size of explanatory variables because it is based on a single step maximum likelihood (ML) procedure. However, because our second step analysis includes more than 700 variables (e.g., dummies for industry and location) it cannot be estimated with the available ML based procedures.

For these reasons, we take advantage of the panel character of our data and measure technical inefficiency as a firm-specific effect.[5] The basic specification is a deterministic transcendental logarithmic (translog) production function, which can be written as (see Greene 1997):

$$\ln y_{it} = \ln \alpha_i + \lambda_t + \sum \beta_k \ln x_{kit} + \sum \beta_{2\_k} \left(\ln x_{kit}\right)^2 + \frac{1}{2}\sum_{q \neq w} \gamma_{qw} \left(\ln x_{qit}\right)\left(\ln x_{wit}\right) + \varepsilon_{it} \qquad (1)$$

where $k=1,\ldots,p$, $i=1,\ldots,N$, $t=1,\ldots,T_i$ and $q=1,\ldots,p$, $w=1,\ldots,p$, $q \neq w$. The term y_{it} represents output of firm i in period t; x_{kit} denotes production input k and λ_t represents a time-specific effect. We have N firms and T_i observations for each firm. The assessment of technical efficiency is based on the firm-specific fixed effects α_i. The largest estimate of a firm-specific fixed effect $\max \hat{a}_j$ is used as a benchmark value that represents the highest attainable efficiency level. Technical efficiency TE_i of firm i is then calculated as:

$$\hat{TE}_i = \frac{\hat{\alpha}_i}{\max \hat{\alpha}_j} \cdot 100 \quad [\%] \qquad (2)$$

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[4] An exception is Carree (2002) who proposes a stochastic frontier model with positive skewness of technical efficiency. However, we are not aware of any empirical application so far using this approach.

[5] See Schmidt and Sickles (1984) and Sickles (2005) for a more detailed discussion on such an approach.

At least one firm will meet the benchmark value and the remaining firms will have positive efficiency estimates between 0 and 100 percent.

Several caveats of the fixed effects approach should be mentioned. First, recent developments in efficiency measurement provide models that allow the distinction between a firm's inefficiency and unobserved heterogeneity (see Greene 2005). Accordingly, the fixed effects will not just capture "pure" technical efficiency differences between firms but also other (unobserved) differences, e.g., different management or marketing strategies. However, for our sample of 35,000 firms (see section 4), Greene's approach is computationally too demanding.[6] Second, our approach implies that the estimated technical efficiency is constant over the period of observation. However, to analyze the dynamics of technical efficiency would reduce the size of the sample considerably because only firms with more than four observations could be included into our model. Furthermore, such an analysis would be dominated by large firms since these firms are sampled more frequently in the Cost Structure Census than the smaller firms (see section 4 for details). Third, we are aware that we do not measure a pure input-output quantity relationship with the production function, since all inputs as well as the output are measured in monetary terms. The reason for this is that prices of inputs and outputs are not available at the firm level. Accordingly, the estimated fixed effects will not only signify that some firms produce higher output than others given input levels, but will also indicate that some firms can obtain higher market prices for their output (or have lower input prices). Our interpretation of this measurement issue is that the fixed effects also measure a type of price efficiency of firms. However, we are confident that using inputs and outputs in monetary terms is not a serious concern of our study. Monetary values allow the aggregation of multiple outputs into a single output and aggregation of different inputs. Moreover, it makes aggregation of inputs and outputs of different qualities feasible, since prices will adjust for those differences.

[6] A further shortcoming of the 'true' fixed effects stochastic frontier model is that it leads to biased parameter estimates and biased estimates of technical efficiencies for panels with relatively few observations as in our case (c.f. to Greene 2005).

To analyze the determinants of technical efficiency, we relate the estimated technical efficiencies to a number of explanatory variables. We apply an Analysis of Covariance (ANCOVA) as a regression method where independent variables can be both metric and categorical. Since categorical variables (e.g., industry affiliation) may have a large number of levels (categories), we do not report the single estimates for each category but report partial *R*-squares for each variable or effect. Partial *R*-squares should be preferred over *t*-statistics in analyses with a large number of observations since the significance of simple *t*-tests do not express the explanatory power of a variable or an effect (cf. McCloskey and Ziliak 1996). Partial *R*-squares[7] express how much of the variation of the dependent variable can be explained by a particular variable or a subset of dummy variables (representing a categorical variable) *given that the other variables are included in the model*. Therefore, partial *R*-squares measure the difference of the models' *R*-square with and without a certain variable or effect.

Since the technical efficiency estimate for each firm is time-invariant, the second step of the analysis is based on the cross-section of firms. All explanatory variables are included as firm-specific averages over the observation period. Knowing the years a firm is included in the sample allows us—even in this cross-sectional setup—to include year dummies. For each firm, a respective year dummy is set to 1 if the firm is observed in that year and is set to 0 otherwise. To estimate year dummies with cross-sectional data is possible because not all firms are observed over the entire period; some firms exit or enter the sample sooner or later than others. Therefore, the year dummies measure the overall trend of the firms' average efficiency. For instance, it could be expected that average efficiency improves over time. If that happens, we should find significantly higher estimates of the year dummy variables for the later years compared to the first years of the sample period.

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[7] Theil (1971) gives both intuition and theoretical grounds for the empirical importance of measuring incremental contributions of the variables' influence on the dependent variable. Furthermore, Flury (1989) and Shea (1997) argue that particularly partial statistics should be taken into consideration when analyzing the relevance of variables in multivariate models. Moreover, Hamilton (1987) emphasizes the merit of partial correlations in determining which explanatory variables to keep in the case of correlated variables.

4. Data

We use the micro-data from the German Cost Structure Census[8] of Manufacturing for the 1992 to 2004 period (cf. Fritsch*, et al.* 2004) of our analysis. The Cost Structure Census is gathered and compiled by the German Federal Statistical Office (*Statistisches Bundesamt)*. The survey consists of all of the large German manufacturing firms which have 500 or more employees over the entire period. In order to limit the reporting effort of the smaller firms to a reasonable level, firms with 20-499 employees are included only as a random sample that can be assumed as being representative for this size category as a whole. Firms with less than 20 employees are not included.[9] As a rule, the smaller firms report for four subsequent years and are then substituted by other small firms (rotating panel).[10] Because the estimation of firm-specific fixed effects requires at least two observations, firms with only one observation are excluded, thus, leaving approximately 35,000 firms in the sample. Table 1 shows the frequency of firms with different numbers of observations in our data set.

Note that the industry classification changed in 1995 from WZ1979 to WZ1993, where the latter corresponds to the international NACE classification. We kept only those firms in the sample for which an industry affiliation according to WZ1995 is available, i.e., which have at least one observation after the year 1994. Furthermore, in the second step analysis of the determinants of efficiency we excluded all firms which changed industry affiliation, location or legal form during the observation period.

[8] Aggregate figures are published annually in *Fachserie* 4, *Reihe* 4.3 of the German Federal Statistical Office (various years).

[9] Since the year 2001 the statistics also contain firms with 1-19 employees. These firms are, however, not included in our analysis due to a rotating sampling scheme; only one observation is available for most of these small firms.

[10] Due to mergers or insolvencies, some firms have less than four observations. Note: firms are, however, legally obligated to respond to the Cost Structure Census; thus, there are actually almost no missing observations due to non-response.

Table 1 : Frequencies of firm-year observations in Cost Structure Census

Number of observations (years)	Number of firms	Share of all firms (percent)	Cumulative number of firms	Cumulative share of all firms (percent)
2	25,734	13.22	25,734	13.22
3	17,556	9.02	43,290	22.23
4	25,636	13.17	68,926	35.40
5	18,595	9.55	87521	44.95
6	26,046	13.38	113,567	58.33
7	20,559	10.56	134,126	68.89
8	11,088	5.69	145,214	74.58
9	12,087	6.21	157,301	80.79
10	6,700	3.44	164,001	84.23
11	9,900	5.08	173,901	89.32
12	3,732	1.92	177,633	91.23
13	17,069	8.77	194,702	100.00
Total	194,702	100.00	--	--

We use the value of gross production net of subsidies and excise taxes as a measure of output. This mainly comprises the turnover plus the net-change of the stock of the final products. We do not include turnover from goods for resale as well as from activities that are classified as miscellaneous like license fees, commissions, rents, leasing and etc. because we assume that such revenue cannot adequately be explained on the basis of a production function.

The cost structure census contains information on a number of input categories. These categories are payroll; employers' contribution to the social security system; fringe benefits; expenditures for material inputs, for self-provided equipment, for 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. Further information available in the Cost Structure Census includes industry affiliation, type of business (craft or manufacturing); location of headquarter; value of the stock of raw materials, of the stock of goods for resale and of the stock of final output; R&D

expenditure and the number of R&D employees.[11] The information on employment comprises the number of owners actively working in the firm, the number of employees, part-time employees, home workers and the number of temporary workers.

Table 2: Production shares of inputs – descriptive statistics

Variable	Minimum	0.5th percentile	Median	99.5th percentile	Maximum
Material inputs	6E-07	0.0050	0.381	0.90	661
Labor compensation	3E-03	0.0440	0.351	1.16	2177
Energy consumption	0	0.0003	0.014	0.23	325
Capital	9E-09	0.0058	0.061	0.39	377
External services	2E-06	0.0008	0.031	0.43	188
Other inputs	3E-05	0.0075	0.087	0.59	329

Note: Number of observations 214,746

Median production shares of these input categories and other descriptive statistics are reported in Table 2. The dominant categories are material inputs and payroll; the median values of which add up to about 73 percent of the overall expenses. The median values of the shares sum up to 0.93. The difference to unity of approximately 7 percent can be interpreted as the share of gross profits in production. Since firms with less than 500 employees are only included in the Cost Structure Census as a representative random sample, we use weights greater or equal to one for the estimation of the production for the firms in these size categories. Each of these firms is multiplied by a factor that represents the relationship between the number of firms in an industry and size category in the full population, the number of firms of the respective industry and size that is included in our

[11] Since 1999, information on the resources devoted to R&D is compiled in the Cost Structure Census.

sample.[12] Since these weights are rather stable over time, we use the weights for the year 1997 in all of the estimations.

Table 3: Descriptive statistics of inputs and outputs

Variable	Mean	St. Dev	Coeff. of variation	Minimum	1st Quartile	Median	3d Quartile	Maximum
Ouput	16.86	1.48	8.77	12.34	15.76	16.68	17.80	25.24
Material inputs	15.76	1.76	11.15	8.05	14.57	15.68	16.91	24.87
Labor compensation	15.74	1.36	8.64	11.50	14.72	15.53	16.56	23.86
Energy consumption	12.62	1.69	13.43	6.52	11.38	12.44	13.71	22.17
Capital	14.05	1.50	10.68	8.95	13.00	13.92	14.98	22.47
External services	14.37	1.74	12.09	8.18	13.12	14.24	15.50	23.32
Other inputs	13.36	1.96	14.67	6.44	9.14	13.33	14.69	21.97

Note: Number of observations 194,702

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 since many firms do not utilize these types of input. Since all inputs in a translog production function are included in logarithms, such zero values for certain input categories would 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 translog production technology and would imply zero output. In order to reduce the number of reported zero input values, we aggregated the inputs into the following broader categories: material inputs (intermediate material consumption), labor compensation (salaries and

[12] 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.

wages plus employer's social insurance contribution), energy consumption, capital input (depreciation of fixed assets plus rents and leases), external services (e.g., repair costs and external wage-work) 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 3 presents the basic descriptive statistics for logarithmic values of output and all input categories.

Table 4: Names and definitions of variables

Name	Description
Factors external to the firm	
- Industry affiliation	Industry dummies at the 4-digit level (255 industries)
- Location	District (*Kreis*) of the headquarter of the enterprise (441 districts)
- Year effects	Dummy variable for each year, 1992-2004
- Share in industry	Relative production share of German suppliers in the respective industry
Factors internal to the firm	
a) Firm characteristics	
- Size	Six categories: less then 49 employees (= 1), 50-99 employees (= 2), 100-249 employees (= 3), (iv) 250-499 employees (= 4), 500-999 employees (= 5), more than 1000 employees (=6)
- R&D intensity	Share of R&D personnel over total employment (available from 1999 on)
b) Outsourcing activities	
- Quota of external contract work	Expenditure for external contract work / internal labor cost
- Quota of external services	Expenditure for external services / internal labor cost
- Quota of material inputs	Expenditure for material inputs / internal labor cost
- Quota of temporarily employed labor	Expenditure for temporary employed labor / internal labor cost; available from 1999 on
- Quota operating leases	Operating leasing expenses / capital depreciations (available from 1999 on)
c) Ownership and legal form	
- Type of business	Manufacturing (=1) / craft (=0) dummy variable
- Legal form	Non-corporate (=1) or corporate company (=8), other legal form (=9)
- Number of owners working in the firm	Number of owners working in the firm

After including the yearly values of the depreciations as a proxy for capital input, it causes a rather low estimate for the elasticity of the capital input. The obvious reason for this low value is the relatively high year-to-year variation of the depreciations. In order to reduce this volatility, we calculated the average yearly depreciations for each year by adding up the depreciations in the current year and of all the preceding years that we have in our data. This sum was then divided by the number of respective years.[13] By using such average values of yearly depreciation, the result is a considerably higher estimate of the output elasticity of capital. Table 4 gives an overview on the firm-level information available in the Cost Structure Census that is included in our analyses.

The sample contains a number of observations with extreme values (see maximum and minimum columns in Table 2) that proved to have a considerable impact on the estimated parameters of the production function and lead to implausible results. Therefore, we exclude such 'outliers' from the analysis for which the cost for a certain input category in relation to gross value added is less than the lowest 0.5 percent and the highest 99.5 percent. In total, these excluded cases (plus firms with zero values for at least one input category) make about 10 percent of all observations. We find that the exclusion of these extreme cases leads to a considerable improvement of robustness and plausibility of the estimation results for the production function.

5. Empirical results

5.1 Production function estimation

Table 5 displays the parameter estimates of a translog production function according to equation (1) based on the micro-data for individual firms.[14] We included dummy

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[13] Example: Assume that the data set provides information on depreciations of a certain firm for the years 1993, 1994, 1995 and 1996. Average yearly depreciation for the year 1995 is the average of the years 1993 - 1995. For the year 1996 it is the average of the years 1993 - 1996 etc. For the year 1993 the average equals the value for this year.

[14] Least Squares Dummy Variables method for panel data; see Baltagi (2001) and Coelli, *et al.* (2002) for details on this approach.

variables for the different years of the observation period, with 2004 as the year of reference. The fit of the regression (R^2) is remarkably high (0.996) and the fixed firm-effects as well as the year-effects are highly significant.[15]

Table 5: Estimates for logarithmic translog production function with fixed effects

Variable	Coefficient	p-value	Variable	Coefficient	p-value	Variable	Coefficient	p-value
β_mat	0.217	<.0001	γ_mat_ene	-0.004	<.0001	γ_oth_ext	-0.001	0.0132
β_lab	0.270	<.0001	γ_mat_cap	-0.018	<.0001	1992 dummy	0.025	<.0001
β_ene	0.021	0.0184	γ_mat_oth	-0.017	<.0001	1993 dummy	0.012	<.0001
β_cap	0.206	<.0001	γ_mat_ext	-0.017	<.0001	1994 dummy	0.015	<.0001
β_oth	0.161	<.0001	γ_lab_ene	-0.004	0.0002	1995 dummy	0.019	<.0001
β_ext	0.126	<.0001	γ_lab_cap	-0.025	<.0001	1996 dummy	0.014	<.0001
β_2_mat	0.083	<.0001	γ_lab_oth	-0.029	<.0001	1997 dummy	0.015	<.0001
β_2_lab	0.087	<.0001	γ_lab_ext	-0.014	<.0001	1998 dummy	0.015	<.0001
β_2_ene	0.008	<.0001	γ_ene_cap	0.0001	0.8953	1999 dummy	0.018	<.0001
β_2_cap	0.025	<.0001	γ_ene_oth	-0.003	<.0001	2000 dummy	0.014	<.0001
β_2_oth	0.029	<.0001	γ_ene_ext	-0.002	<.0001	2001 dummy	0.005	0.0007
β_2_ext	0.018	<.0001	γ_cap_oth	-0.010	<.0001	2002 dummy	-0.005	0.0012
γ_mat_lab	-0.103	<.0001	γ_cap_ext	-0.003	<.0001	2003 dummy	-0.004	0.0006
		R^2	0.996					
	Number of observations		194,702					

Notes: Mat: material inputs, lab: labor compensation, ene: energy consumption, cap: capital, oth: other inputs, ext: external services.

Several specification tests were performed. First, we investigated if the translog specification is superior to a simple Cobb-Douglas specification. Accordingly, the null hypothesis is $\beta_{2\_i} = 0$ and $\gamma_{ij} = 0$ for all i and j. This null hypothesis is strongly rejected (*p-value* < 0.0001) indicating that the translog specification is more appropriate. Second, the

[15] Note: the results of a Hausman-Wu test indicate 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.

H_0 that ($\Sigma\beta_{2\_i}+\Sigma\gamma_{ij}$) ($j\neq i$) is equal to zero[16] is not rejected (*p-value* = 0.37). This indicates a homothetic production technology; i.e., the marginal rate of technical substitution is homogeneous of degree zero with regard to inputs. Third, given homotheticity and because the test of H_0 that $\Sigma\beta=1$ yields a *p-value* of 0.89, we conclude that the estimated technology is linearly homogeneous.[17]

Table 6: Output elasticities of input factors at different input levels

Input factor	Output elasticity at input level		
	25% (Q1)	50% (Median)	75% (Q3)
Material inputs	0.408	0.446	0.475
Labor compensation	0.395	0.343	0.308
Energy consumption	0.023	0.027	0.032
Capital	0.074	0.065	0.054
External services	0.069	0.078	0.084
Other inputs	0.047	0.061	0.069
Sum	1.016	1.019	1.021

Output elasticities can be calculated from the translog estimates using the formula $\hat{\sigma}_{yi} = \partial \ln y \big/ \partial \ln x_i = \beta_i + \beta_{2\_i} \ln x_i + \sum_{\substack{j \\ i\neq j}} \beta_{ij} \ln x_j$. The output elasticities at different values of production inputs (25, 50 and 75 quantiles) are shown in Table 6. It is worth noting that they add up to about unity and are not very different from median production shares of production inputs as reported in Table 2, which could be expected according to neoclassical theory (see Chambers 1988).[18] This again supports the plausibility of our production function estimates. Using a proxy variable instead of a direct measure of the

[16] This sum of estimates is 0.000495 with a standard error of 0.00055.

[17] The sum of single input estimates is 1.0023 with a standard error of 0.01625.

[18] Although the elasticities vary considerably at different input levels, the sum is always about one. This is due to the fact that the elasticities are obtained from parameter estimates which are in accordance with a homothetic production function.

capital stock input could be a potential concern. However, even with a crude proxy based on the depreciations for the capital input, the obtained elasticity of capital appears to be quite reasonable. The positive values of most of the year dummies (Table 5) indicate a higher productivity in the respective year compared to the reference year 2004. We assume that these dummies are not simply a measure of technical progress because the ongoing advancement over time would imply negative values of the year dummies. Accordingly, the values of the year dummies mainly reflect the macro-economic conditions, which were relatively unfavorable with a considerable underutilization of capacities in 2002 as well as in 2003, in which a negative value for the respective dummy variable is found.

5.2 Variation of technical efficiency in different size categories

The distribution of technical efficiency scores calculated according to equation (2) is centered and most firms are clustered close to the mean (Figure 1). The symmetry of the distribution of technical efficiency makes the second step analysis applying OLS estimation sensible. There is a slight positive skewness of the distribution that is, however, not statistically significant. In each size category, the pattern of the distribution corresponds to the distribution of the whole sample (Figure 2 and Table 7). The mean of the efficiency value is gradually decreasing with firm size while the coefficient of variation tends to be increasing. This suggests that firm size might have an effect on the structure of the technical efficiency distribution. Thus, large firms are on average more inefficient than smaller ones and the variation of efficiency is larger within the group of large firms. Our interpretation of the larger heterogeneity of efficiency within the group of large firms is that inefficient large firms are able to survive for a longer period of time while smaller inefficient firms, due to financial constraints, are more likely to exit the market in a shorter time frame.

Table 7: Distribution of technical efficiency in different size categories

Statistic				*Size category*			
	Total	<49	50-99	100-249	250-499	500-999	>1000
Mean	0.538	0.557	0.540	0.524	0.511	0.496	0.479
Coefficient of variation	0.138	0.133	0.131	0.131	0.137	0.145	0.140
Skewness	0.461	0.532	0.344	0.412	0.887	0.612	0.399
Kurtosis	6.196	6.384	6.664	6.590	8.794	7.284	4.437
Maximum	1.000	1.000	1.000	1.000	1.000	1.000	0.757
95th percentile	0.658	0.677	0.653	0.633	0.623	0.621	0.604
90th percentile	0.622	0.641	0.618	0.599	0.588	0.577	0.563
75th percentile (Q3)	0.576	0.592	0.574	0.557	0.542	0.527	0.511
Median	0.536	0.554	0.538	0.522	0.508	0.493	0.474
25th percentile (Q1)	0.499	0.520	0.506	0.489	0.475	0.460	0.443
10th percentile	0.455	0.476	0.461	0.447	0.437	0.421	0.405
5th percentile	0.419	0.439	0.421	0.413	0.405	0.384	0.372
Minimum	0.202	0.258	0.202	0.237	0.232	0.240	0.277
Number of observations	35,108	13,965	8,913	7,385	2,696	1,372	777

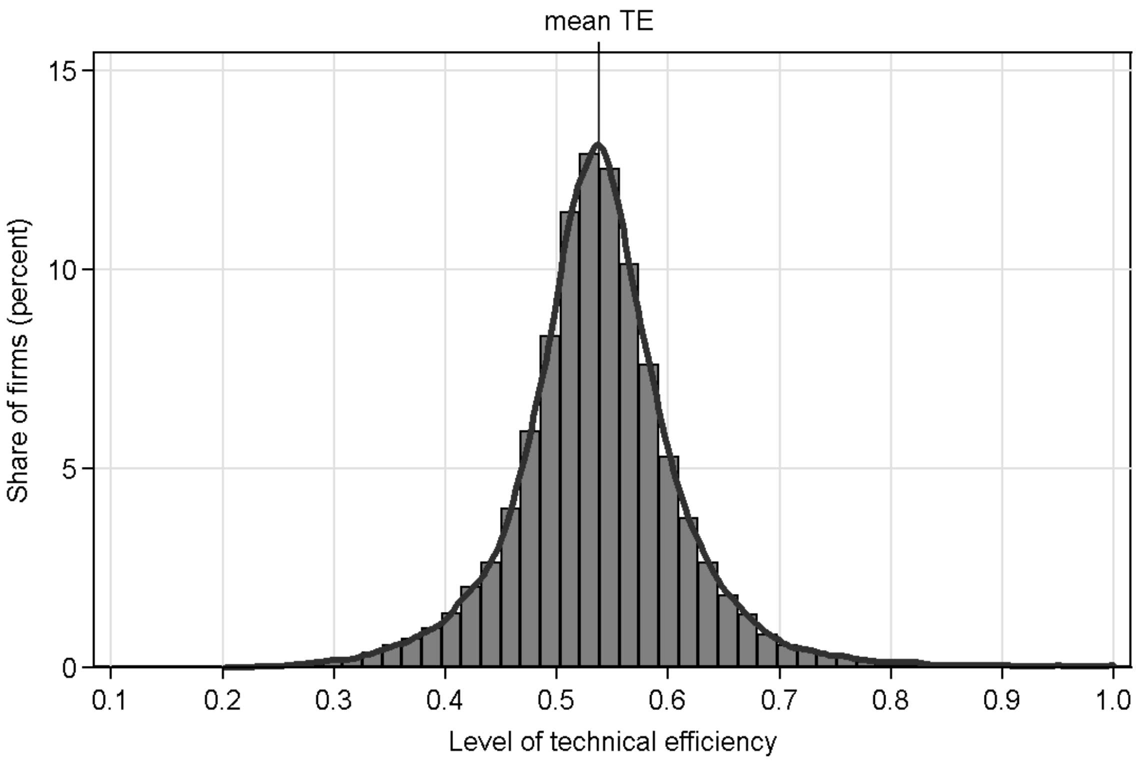

Figure 1: Histogram and kernel density of technical efficiency at the micro-level (35,108 observations)

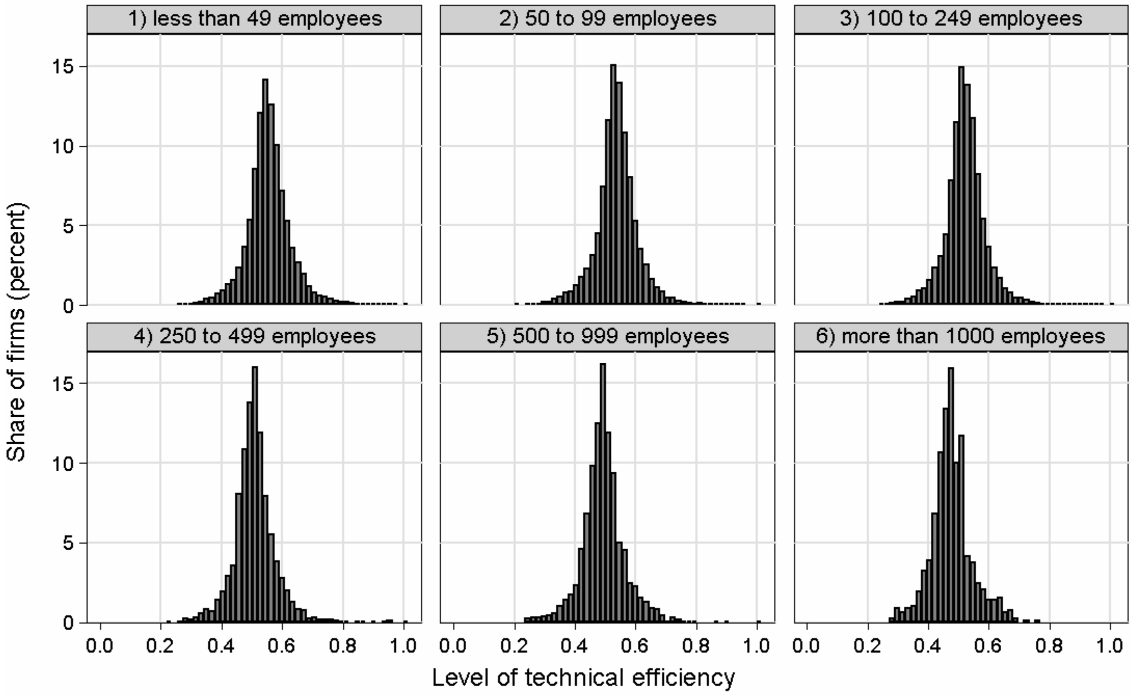

Figure 2: Distribution of technical efficiency in different size categories

5.3 Determinants of technical efficiency

Table 8 displays the partial *R*-square values which indicate the relative importance of a variable for the entire observation period, 1992-2004 and for the last six years, i.e., 1999-2004. Conducting the analyses for the 1999 to 2004 period separately allows the inclusion of information on R&D intensity and temporarily employed (sub-contracted) labor, which is only available from the years 1999 onward. Table 9 provides the signs, magnitudes and *t*-values for all continuous and for some selected categorical variables. Note: we include the number of observation periods as a control variable for sample selection. A potential concern might be that each year some firms exit the market and are not contained in the sample anymore. If these exiting firms are characterized by a relatively poor efficiency performance, the sample could be biased. In this case, we should find a significantly positive relationship between efficiency and the number of observation periods. Indeed,

Table 8: Partial *R*-squares (in percent) for variables

Variable	Time period			
	1992-2004		1999-2004	
	Df	Partial *R*-square	Df	Partial *R*-square
Factors external to the firm				
Industry affiliation	256	7.80*	255	8.02*
Location (district)	441	2.30*	441	2.32*
Year-effects	13	0.33	6	0.36
Share in industry	1	0.0005	1	0.0007
Factors internal to the firm				
a) Firm characteristics				
Size category	5	6.12*	5	5.07*
Number of owners working in the firm	1	0.13*	1	0.14*
R&D intensity (expenditures)	—	—	1	0.21*
b) Outsourcing activities				
Quota of material inputs	1	0.04*	1	0.24*
Quota of external contract work	1	0.38*	1	0.45*
Quota of external services	1	0.08*	1	0.03*
Quota of temporarily employed labor	—	—	1	0.002
Quota rents and leases	—	—	1	0.001
c) Legal form				
Legal form	2	0.11*	2	0.11*
Sample selection control				
Number of years observed	1	0.19*	1	0.02*
Overall *R*-square	24.40		23.50	
Sum of all partial *R*-squares[19]	17.48		16.96	
Number of observations	35,108		21,499	

Notes: Dependent variable: technical efficiency; Df: degrees of freedom; *: statistically significant at the 1 percent level.

[19] The larger the difference between the overall *R*-square and sum of all partial R-squares is, the closer the statistical relationship between the included explanatory variables is.

Table 9: Parameter estimates (*t*-values in parentheses) for selected variables[20]

Variable	Time period	
	1992-2004	1999-2004
Factors external to the firm		
Share of industry	-0.015 (-0.47)	-0.015 (-0.44)
Factors internal to the firm		
a) Size category		
less than 49 employees	0.169* (31.06)	0.149* (24.40)
50-99 employees	0.130* (24.19)	0.119* (19.89)
100-249 employees	0.096* (18.03)	0.090* (15.27)
250-499 employees	0.067* (12.17)	0.063* (10.45)
500-999 employees	0.034* (5.82)	0.037* (5.86)
more than 1000 employees	-	-
Number of owners working in the firm	0.010* (7.77)	0.009* (6.09)
R&D intensity (expenditures)	-	-0.145* (-7.55)
b) Outsourcing activities		
Quota of material inputs	-0.002* (-4.28)	-0.005* (-8.14)
Quota of external contract work	0.039* (13.21)	0.037* (11.02)
Quota of external services	0.053* (5.97)	0.030* (2.69)
Quota of temporarily employed labor	-	-0.014 (-0.70)
Quota rents and leases	-	7.06E-06
c) Legal form		
Non-corporate firm	0.003 (0.21)	0.001 (0.05)
Corporate firm	-0.011 (-0.88)	-0.012 (-0.75)
Other legal form	-	-
Sample selection control		
Number of years observed	0.010* (9.20)	-0.001* (2.50)
Number of observations	35,108	21,499

Note: *: statistically significant at the 1 percent level

the number of observation periods turns out to be significant in some of the specifications, but with a rather low explanatory power in terms of partial *R*-square. Hence, we conclude that there is some sample selection bias due to a higher propensity of inefficient firms to drop out the sample but that this bias is not a severe concern in these cases. Interestingly,

[20] It is not possible to present all estimates, since ANCOVA gives an estimate for every category of a nominal variable, resulting in 253 estimates for each industry, 9 estimates for each region type etc. Estimates for all categories are available from the authors upon request.

the number of observations has a larger explanatory power for the sample of least efficient firms (reported in Table 12) than for the group of most efficient firms.

For the 1992-2004 period, all included independent variables have significant explanatory power at the one percent level (except share in industry and year effects). However, with regards to the magnitudes of partial *R*-squares, we can state that industry affiliation, firm size and location are by far the most important effects on technical efficiency. The great importance of industry effects is in line with the findings of studies which emphasize the role of industry for explaining firm profitability (Cubbin and Geroski 1987, Schmalensee 1985). Industry effects might capture different degrees of competition in the single industries or might accrue from different stages of the industry life cycle or different technological regimes (Fritsch and Stephan 2004). We find that year dummy variables are significant but with a rather low explanatory power. Moreover, the estimated parameters (not reported) do not indicate a trend of increasing overall efficiency over the sample period. Our interpretation of this result is that some firms improve their efficiency whereas other firms become less efficient; thus, the net effect might be zero. This could explain why we do not find an improvement of average efficiency over time.

Table 10 gives an overview of the most and the least efficient industries according to the parameter estimates of the corresponding dummy variables. Among the most efficient industries, several are from the NACE category 22 “publishing, printing and reproduction of recorded media.” Three of the least efficient industries belong to the NACE category 17 “manufacture of textiles,” an industry of declining importance in Germany.

It is important to note that firm size explains 25 percent of the variation of technical efficiency across firms for the entire period and 22 percent for the shorter period 1999-2004. This finding confirms results of other studies that showed different efficiency performance of firms in different size classes (e.g., Alvarez and Crespi 2003, Caves 1992, Torii 1992). However, our results strongly contradict these studies with regard to the direction of this size effect: according to our analysis firms become less efficient as size increases. Thus, smaller firms are significantly more efficient than larger ones (Table 9).

Table 10: The most and the least efficient industries

Efficiency Rank	*NACE*	*Description*
1	1110	Extraction of crude petroleum and natural gas
2	2652	Manufacture of lime
3	2651	Manufacture of cement
4	2211	Publishing of books
5	2941	Manufacture of machine tools
6	2212	Publishing of books and newspapers
7	2214	Publishing of sound recordings
8	2640	Manufacture of bricks, tiles and construction products
9	2224	Composition and plate-making
10	1421	Operation of gravel and sand pits
11	2851	Treatment and coating of metals
12	2213	Publishing of journals and periodicals
13	2330	Processing of nuclear fuel
14	2442	Manufacture of pharmaceutical preparations
15	2225	Other activities related to printing
16	2232	Reproduction of video recording
17	1440	Production of salt
18	2625	Manufacture of other ceramic products
19	1412	Quarrying of limestone, gypsum and chalk
20	2441	Manufacture of basic pharmaceutical products
…	…	…
250	2465	Manufacture of prepared unrecorded media
251	1562	Manufacture of starches and starch products
252	1712	Preparation and spinning of woolen-type fibers
253	1716	Manufacture of sewing threads
254	2411	Manufacture of industrial gases
255	1430	Mining of chemical and fertilizer minerals
256	1713	Preparation and spinning of worsted-type fibers
257	1010	Mining and agglomeration of hard coal

The location effect is captured by including 441 dummy variables for the German districts (*Kreise*). It is worth noting that with this approach we do not only capture differences in the performance of the firms located in the Eastern or Western part of Germany (e.g., Funke and Rahn 2002), but that we assess the efficiency of firms at a much smaller geographical scale. The results for firm location suggest that regional factors play a rather important role. The explanatory power of location in terms of partial *R*-square is 9.4 percent for the 1992-2004 period and 9.9 percent for the 1999-2004 period. The location variable refers to the firm's headquarter and not to the location of branch plants which may be located in other regions. However, since more than 90 percent of the firms in the Cost Structure Census are single-establishment firms, a disturbing effect of branch plants located in other regions cannot be very strong. Table 11 shows the most and the least efficient districts according to the parameter estimates of the corresponding dummy variable. While all of the most efficient districts are located in the western part of Germany, the least efficient districts are all in the East.

Table 11: The most and least efficient locations

Rank	County name	Federal State	East/West
1	Eichstätt	Bavaria	West
2	Wittmund	Lower Saxony	West
3	Ebersberg	Bavaria	West
4	KS Wolfsburg	Lower Saxony	West
5	Kronach	Bavaria	West
6	Freyung-Grafenau	Bavaria	West
7	KS Coburg	Bavaria	West
8	Lichtenfels	Bavaria	West
9	KS Koblenz	Rhineland-Palatinate	West
10	Muehldorf a. Inn	Bavaria	West
…	…	…	…
432	KS Suhl	Thuringia	East
433	Riesa-Großenhain	Saxony	East
434	Chemnitz-Stadt	Saxony	East
435	Nordvorpommern	Mecklenburg-Western Pomerania	East
436	Barnim	Brandenburg	East
437	KS Berlin (East)	Berlin	East
438	Wittenberg	Saxony-Anhalt	East
439	KS Stralsund	Mecklenburg-Western Pomerania	East
440	Märkisch Oderland	Brandenburg	East
441	KS Magdeburg	Saxony-Anhalt	East

Firm size is the only firm-specific determinant that can explain a larger part of the technical efficiency (Table 8). Other factors such as the share of R&D expenditure, the legal form of the firm or indicators for the degree of outsourcing are not very important. The parameter estimates (Table 9) show a negative effect of R&D on technical efficiency.[21] This confirms the empirical findings by Albach (1980) and Caves and Barton (1990), but it is also counter-intuitive since R&D should lead to improved products or cost reduction (Aghion and Howitt 1992, Grossman and Helpman 1991). An explanation for the negative sign of the impact of R&D activity on technical efficiency is that there may be a considerable time lag between R&D spending and the occurrence of the results (Helpman 1992). If this is the case, R&D expenditure only represents additional costs at the time it is made, thereby, reducing technical efficiency while the benefits can be appropriated only at later time periods. [22] Unfortunately, we cannot test for such time lags because information on R&D activity is only available in our data for the most recent years.

We also conducted the analyses for the sub-samples of the 10 percent least efficient firms, the 10 percent most efficient firms and firms with an efficiency level between these groups with relatively high and low efficiency values (Tables 12 and 13). It is most remarkable that the significance as well as the relative importance of certain influences changes enormously when we look at three different groups of firms. In comparison to the results for all firms, the estimates for the sub-groups show that many of the previously statistically significant effects are not important for particular groups of firms. For example, size has a much stronger impact in the group of firms with medium efficiency as compared to the 10 percent least efficient and 10 percent most efficient firms. At the same time, industry effects are even stronger in the groups of relatively efficient and relatively inefficient firms. Most remarkable, location explains more than a half of the variation of technical efficiency within the sub-sample of the relatively inefficient firms while it loses its explanatory power almost completely for the firms with a medium and a relatively

[21] We tested two alternative measures of R&D intensity: (1) share of R&D personnel to total employment, (2) cumulated R&D expenditures (R&D capital stocks). The findings for R&D are robust with respect to these alternative measures.

[22] There are a number of problems related to the measurement of R&D input and particularly the output of innovation activity that make the identification of the relationship rather difficult (c.f. Griliches 1995). Note, that in contrast to other studies which in most cases found a slightly positive impact of R&D investment on productivity, our dependent variable, the efficiency, measures the relative productivity performance of a firm.

Table 12: Partial *R*-squares (in percent) for the 10 percent least efficient firms, the 10 percent most efficient firms and firms between the 10 percent least and 10 percent most efficient firms

Variable	Time period											
	1992-2004						1999-2004					
	(I)		(II)		(III)		(IV)		(V)		(VI)	
	Df	10% least efficient	Df	Between 10% least and most efficient	Df	10% most efficient	Df	10% least efficient	Df	Between 10% least and most efficient	Df	10% most efficient
Factors external to the firm												
Industry affiliation	228	8.44*	256	5.05*	211	10.35*	206	16.63*	255	5.62*	204	11.27*
Location (district)	430	12.63*	441	2.11*	432	10.63	377	23.51	441	2.56*	414	16.18
Year-effects	13	0.97	13	0.19	13	1.00	6	0.27	6	0.21	6	0.75
Share of industry	1	0.04	1	0.003	1	0.19*	1	0.07	1	0.001	1	0.17
Factors internal to the firm												
a) Firm characteristics												
Size category	5	0.63*	5	6.69*	5	0.50*	5	0.20	5	6.13*	5	0.73*
Number of owners working in the firm	1	0.04	1	0.28*	1	0.01	1	0.19	1	0.32*	1	0.04
R&D intensity (expenditures)	—	—	—	—	—	—	1	0.12	1	0.13*	1	0.004
b) Outsourcing activities												
Quota of material inputs	1	2.40*	1	0.17*	1	0.52*	1	0.82*	1	0.17*	1	0.76*
Quota of external contract work	1	0.17*	1	0.08*	1	1.01*	1	0.005	1	0.08*	1	0.52*
Quota of external services	1	0.16*	1	0.01	1	0.17*	1	0.03	1	0.0008	1	0.28*
Quota of temporarily employed labor	—	—	—	—	—	—	1	0.04	1	0.02	1	0.004
Quota rents and leases	—	—	—	—	—	—	1	0.02	1	1.50E-04	1	0.02
c) Legal form												
Legal form	2	0.07	2	0.01	2	0.65*	2	0.08	2	0.01	2	1.01*
Sample selection control												
Number of years observed	1	2.26*	1	0.03*	1	0.01	1	1.57*	1	0.17*	1	0.14
Overall *R*-square	31.73		19.79		27.71		47.67		21.90		36.39	
Sum of all partial *R*-squares	27.81		14.62		25.03		43.54		15.25		31.88	
Number of observations	3,432		28,041		3,635		1,476		17,753		2,270	

Notes: Dependent variable: technical efficiency; Df: degrees of freedom; *: statistically significant at the 1 percent level

Table 13: Parameter estimates (*t*-values in parentheses) of selected variables for the 10 percent least efficient firms, the 10 percent most efficient firms and firms between the 10 percent least and 10 percent most efficient firms

Variable	Time period					
	1992-2004			1999-2004		
	(I)	(II)	(III)	(IV)	(V)	(VI)
	10% least efficient	b/n 10% and 90%	10% most efficient	10% least efficient	b/n 10% and 90%	10% most efficient
Factors external to the firm						
Share of industry	-0.079 (-1.30)	-0.020 (-0.94)	0.303* (2.77)	-0.082 (-1.05)	-0.011 (-0.49)	0.262 (2.10)
Factors internal to the firm						
a) Size category						
less than 49 employees	0.035* (3.18)	0.089* (24.65)	0.074* (4.02)	0.009 (0.54)	0.087* (20.76)	0.087* (3.90)
50-99 employees	0.021 (1.92)	0.071* (19.95)	0.069* (3.74)	0.012 (0.82)	0.072* (17.56)	0.083* (3.71)
100-249 employees	0.017 (1.60)	0.049* (13.98)	0.064* (3.45)	0.017 (1.23)	0.050* (12.53)	0.075* (3.38)
250-499 employees	0.001 (0.08)	0.028* (7.60)	0.064* (3.36)	0.012 (0.79)	0.029* (6.97)	0.067* (2.91)
500-999 employees	0.002 (0.20)	0.012* (3.17)	0.047 (2.25)	-0.001(-0.09)	0.015* (3.37)	0.057 (2.33)
more than 1000 employees	-	-	-	-	-	-
Number of owners working in the firm	-0.005 (-1.25)	0.008* (9.83)	0.001 (0.47)	-0.011 (-1.79)	0.008* (8.30)	0.004 (1.00)
R&D intensity (expenditures)	-	-	-	-0.069 (-1.38)	-0.067* (-5.23)	0.019 (0.32)
b) Outsourcing activities						
Quota of material inputs	0.022* (9.82)	-0.002* (-7.51)	-0.008* (-4.61)	0.012* (3.68)	-0.002* (-6.10)	-0.011* (-4.42)
Quota of external contract work	0.036* (2.59)	0.010* (5.21)	0.031* (6.44)	0.006 (0.28)	0.010* (4.21)	0.023* (3.66)
Quota of external services	-0.070* (-2.57)	0.010 (1.74)	0.040* (2.64)	-0.025 (-0.66)	-0.003 (-0.42)	0.074* (2.68)
Quota of temporarily employed labor	-	-	-	0.083 (0.80)	-0.029 (-2.25)	-0.017 (-0.30)
Quota rents and leases	-	-	-	-0.0002 (-0.53)	0.000001 (0.18)	-0.00003 (-0.62)
c) Legal form						
Non-corporate firm	-0.019 (-0.53)	0.005 (0.68)	-0.261* (-4.12)	-0.020 (-0.22)	-0.001 (-0.06)	-0.450* (-4.70)
Corporate firm	-0.028 (-0.80)	0.003 (0.37)	-0.273* (-4.33)	-0.030 (-0.34)	-0.002 (-0.23)	-0.460* (-4.81)
Other legal form	-	-	-	-	-	-
Sample selection control						
Number of years observed	0.024* (9.53)	-0.002* (3.02)	-0.001 (-0.60)	0.007* (5.1)	-0.002* (-6.08)	-0.002 (-1.91)
Number of observations	3,432	28,041	3,635	1,476	17,753	2,270

Notes: Dependent variable: technical efficiency; *: statistically significant at the 1 percent level.

high level of efficiency. This indicates that the locational conditions may have an important effect on firms which have a relatively poor productivity performance but that firms which are performing well do not strongly rely on the characteristics of their location. However, in contrast to the results for the entire sample, the parameter estimates for the districts in the estimates for sub-sample are not clearly separated into East German (low efficiency) and West German (high efficiency) districts. For this sub-sample we find a mixture of East and West German districts, indicating that the location effect we find for this group of relatively inefficient firms is not due to East or West German location but rather is caused by other reasons.

There are some remarkable differences of the signs of the coefficients between the estimates for the sub-groups of firms (Table 13). For example, the quota of material inputs has a positive impact for the least efficient firms but is negative for the firms with a medium and with a relatively high efficiency level. The quota of external services is negative for the least efficient firms but positive for those firms which are most efficient. For the least efficient and the most efficient firms, the explanatory power of R&D intensity is fairly small and statistically insignificant. Both, partial R-square as well as the coefficient are only statistically significant for the sub-sample of the middle efficient firms. Thus, R&D does not explain any variation of technical efficiency at the two ends of the distribution.

6. Concluding remarks

This paper analyzed the determinants of technical efficiency of German manufacturing firms using a panel of about 35,000 firms between 1992 and 2004. Initially, we obtained estimates of technical efficiency and then performed an Analysis of Covariance in a second step to investigate the determinants of the technical efficiency of firms.

The results of the fixed effects approach for obtaining estimates of technical efficiency appear rather reasonable. The distribution of technical efficiency is symmetric and most of the firms are clustered close to mean value. The analysis reveals that industry effects explain the largest part, more than one third of the model's explanatory power, of technical efficiency variation. This result goes hand-in-hand with the evidence reported in the literature (e.g., Schmalensee 1985). Firm size is the second most important factor that has a strong significant effect on technical efficiency. In contrast to previous studies, we find that smaller firms are more efficient than larger ones. The location of a firm's headquarter is also an important factor that explains another 10 percent of variation in technical efficiency. The explanatory power of firm characteristics such as R&D intensity, outsourcing activity and the legal form is relatively small. Quite surprisingly, we find a negative effect of R&D intensity on technical efficiency, albeit with a very low explanatory power. This result may particularly indicate a time lag between R&D spending and the resulting efficiency improvements.

Our estimates of technical efficiency are time invariant. Nevertheless, the estimated year effects in our analysis do not indicate an increase of average efficiency over time. This might be due to the fact that the sum of firm-level changes of efficiency (positive or negative) gives an overall net effect of zero. However, to investigate the frequency and significance of efficiency changes at the firm level will be an interesting starting point for future research. Such analyses can occur when panel data of firms with longer individual time series become available.

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