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Inefficient or just different? Effects of heterogeneity on bank efficiency scores

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Abstract

In this paper, we show the importance of accounting for heterogeneity among sample firms in stochastic frontier analysis. For a fairly homogenous sample of German savings and cooperative banks, we analyze how alternative theoretical assumptions regarding the nature of heterogeneity can be modeled and the extent to which the respective empirical specifications affect estimated efficiency levels and rankings. We find that the level of efficiency scores is affected in the case of both cost and profit models. On the cost side especially, level and rank correlations show that different specifications identify different banks as being best or worst performers. Our main conclusion is that efficiency studies in general and bank efficiency studies in particular should account for heterogeneity across sample firms. Especially when efficiency measures are employed for policy purposes, a careful choice of models and transparency regarding maximization methods are essential to be able to make inferences about managerial behavior.

Keywords: Heterogeneity, X-efficiency, benchmarking, bank production.
JEL: G21, G34, G14

Non-technical summary

Benchmarking the performance of financial institutions is an important element, for example when monitoring the soundness and stability of financial systems. As in any benchmarking analysis, we should take great care in selecting the appropriate common benchmark in order to obtain meaningful benchmark scores.

To do so, we have to acknowledge that banks may deviate from this benchmark for three reasons: (i) random noise, for example owing to measurement problems; (ii) heterogeneity of institutions, for example owing to size and business mix differences that are independent of inefficiency; (iii) inefficiency, for example owing to suboptimal input demand at prevailing factor prices. To improve our interpretation of these inefficiency scores and ranks, we should try to distinguish between these three reasons as much as possible. In this paper, we therefore address two questions. First, we ask how we can disentangle the three aforementioned sources of deviations from optimal performance. Second, we analyze to what extent heterogeneity has an important impact on the efficiency scores obtained.

To this end, we employ three specifications for a cost and alternative profit frontier, each accounting for heterogeneity in a different manner. We estimate these specifications for German cooperative and savings banks for the period from 1993 to 2003. We account for heterogeneity among regions, banking groups and size classes. We then compare these efficiency scores and ranks to those from a baseline frontier specification that assumes full homogeneity.

Our main results can be summarized as follows. First, we find that we need to account for systematic differences across banks, since estimations improve considerably after including indicators for regions, banking groups and size classes. Even for our high-quality sample of homogeneous banks, both mean cost and profit efficiency deviate from the baseline models up to five percentage points. Second, specifying that heterogeneity influences the position of the frontier or the ability to attain the frontier has a significant impact on efficiency, particularly for the cost frontier models. Finally, we find that the ranking of banks' efficiency across alternative specifications is stable. We argue that those few banks that are highly sensitive to different specifications deserve a case-by-case assessment.

Nichttechnische Zusammenfassung

Die Effizienz von Banken zu messen und untereinander zu vergleichen ist für viele Fragestellungen wichtig, u. a. im Rahmen der Überprüfung der Stabilität eines Finanzsystems. Jede Methode erfordert dabei die sorgfältige Auswahl einer geeigneten *Benchmark*, um aussagekräftige Effizienzmaße und -rangfolgen zu erhalten.

Hierbei gilt es zu berücksichtigen, dass Banken aus drei Gründen von dieser *Benchmark* abweichen können: (i) Zufallsfehler, zum Beispiel auf Grund von Messproblemen; (ii) Heterogenität der Institute, zum Beispiel auf Grund unterschiedlicher Größe und strategischer Ausrichtung, die nichts mit Effizienz zu tun haben; (iii) Ineffizienz, zum Beispiel auf Grund suboptimalen Einsatzes von Produktionsfaktoren. Um die Interpretation von Effizienzmaßen und -rangfolgen zu verbessern, muss so exakt wie möglich zwischen diesen drei Gründen unterschieden werden. Wir untersuchen in diesem Papier daher die zwei folgenden Fragen: Erstens, wie lässt sich zwischen den genannten Ursachen für die Abweichungen von der Benchmark unterscheiden? Zweitens, hat die Heterogenität einen signifikanten Einfluss auf ermittelte Effizienzmaße?

Zu diesem Zweck spezifizieren wir jeweils drei *Cost* und *Profit Frontiers*. Jede Spezifikation berücksichtigt auf unterschiedliche Art und Weise die Heterogenität der Institute. Wir schätzen diese *Frontiers* für Genossenschaftsbanken und Sparkassen in der Zeit zwischen 1993 und 2003 unter Berücksichtigung systematischer Unterschiede zwischen lokalen Märkten, Bankengruppen und Größenklassen. Anschließend vergleichen wir die so ermittelten Effizienzmaße und -rangfolgen mit denen aus einem Basismodell unter der Annahme vollkommener Homogenität der Institute.

Unsere Kernergebnisse lassen sich wie folgt zusammenfassen: Indikatoren für Heterogenität müssen berücksichtigt werden, weil sich dadurch die Schätzungen signifikant verbessern. Selbst für unsere qualitativ hochwertige Stichprobe weicht je nach Modell sowohl die durchschnittliche Kosten- als auch Profiteffizienz um bis zu fünf Prozentpunkte von der des Basismodells ab. Insbesondere Kosteneffizienz ist davon abhängig, auf welche Weise Heterogenität spezifiziert wird: entweder als Determinante der Frontier oder als Determinante der Ineffizienzverteilung. Ersteres bedeutet, dass Heterogenität die Position der Benchmark beeinflußt. Letzteres bedeutet, dass die Fähigkeit, diese Benchmark zu erreichen, von systematischen Unterschieden der Institute beeinflusst ist. Unsere Ergebnisse zeigen jedoch auch, dass geschätzte Effizienzrangfolgen stabil sind. Es empfiehlt sich, dass die wenigen Institute, deren Rang je nach Spezifikation drastisch wechselt, auf Einzelfallbasis untersucht werden.

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Inefficient or just Different? Effects of Heterogeneity on Bank Efficiency Scores[1,2]

1 Introduction

Any study that benchmarks different firms requires the assumption that these firms actually do have a common benchmark. This assumption may seem trivial. But in fact, it is crucial because it reflects the notion that compared firms are similar enough to be compared in the first place. At the same time, in benchmarking analyses we are usually most interested in those firms that are furthest removed from the benchmark. These firms in particular may not share the common benchmark. On the one hand, this could merely reflect poor performance. On the other hand, they may be too "different" to be compared to such a common benchmark unless we account for heterogeneity appropriately. Therefore, the question how to specify the benchmark and how to consider heterogeneity is crucial because it influences efficiency estimates substantially.

In fact, Berger et al. (1993) and Berger and Humphrey (1997) confirm that efficiency scores differ markedly across studies. According to Mester (1993, 1997) and Berger and Mester (1997), the failure to account for heterogeneity is a likely candidate to cause this instability of efficiency results. This issue is our focus in the present paper: to explore how group-specific heterogeneity among sample firms affects both the location of and deviations from the benchmark and how to account for it.

This is important for more than just technical reasons. Because in virtually all studies inefficiency results from suboptimal combinations of input quantities, it is often referred to as managerial efficiency. But the mentioned evidence suggests that some of the deviations from optimal behavior are in fact due to factors outside the direct influence of management. For example, savings banks are not free to choose their region of activity by regulation and banks of different size may face different opportunities and constraints to diversify their credit portfolios compared to large banks. Consequently, controlling for heterogeneity results in efficiency scores that more accurately reflect management's ability to minimize costs and maximize profits.

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In this paper, we therefore follow the recommendation of Berger et al. (1993) and Berger and Humphrey (1997) and analyze group-specific heterogeneity of banks and its potential effects on efficiency results in greater detail. To identify the effect of heterogeneity on efficiency requires to fix three additional benchmark specification choices that may account for the observed instability of efficiency measures: (i) bank production models, (ii) samples, and (iii) empirical specifications. Alternative choices within each of these dimensions affect the level of efficiency scores and, more importantly, the ability to identify best and worst in class relative to the benchmark.[3] To isolate the effect of heterogeneity as much as possible, we choose a common production set and limit ourselves to data on German savings and cooperative banks. This data is unique in its coverage and quality and represents a fairly akin sample of banks regarding for example bank size or customer mix. We hypothesize that even for this sample, the failure to account for systematic differences affects efficiency estimates.

The remainder of this paper is organized as follows. In section 2, we review the empirical evidence on the differences between efficiency scores in banking studies. We focus on the few German country studies to introduce the various possibilities for specifying an efficient frontier. The issue of heterogeneity, its potential role in yielding different efficiency results and alternative ways to incorporate it into the analysis is considered next. In section 3, we introduce a baseline specification and three variants, which control for heterogeneity in different ways. The latter are used to assess the stability of efficiency measures. In section 4, we present the data and discuss whether accounting for heterogeneity matters. In section 5, we present and discuss the results. We conclude in section 6.

2 Literature

Benchmarking bank performance based on efficiency measures is well established in the financial economics literature. Most studies rely on duality to evaluate the efficiency of the production process of a bank by means of a cost or profit function.[4] Employing identical technology, banks choose at given in- and output prices the amount of input quantities to maximize output. Leibenstein (1966) argues that deviations from optimal output are an indication of wasted resources due to management's inability to demand inputs efficiently. This waste due to suboptimal management is coined X-(in)efficiency.

[3] Bauer et al. (1998), Berger et al. (1993) and Greene (1993).

[4] The definition of bank "production" is a matter of ongoing debate. Two alternative models are the intermediation approach (Sealey and Lindley 1977) and the production approach (Benston 1965).

Survey papers by Berger and Humphrey (1997) and Berger et al. (1993) review the large number of studies on the efficiency of US financial institutions throughout the 1990s. Excellent reviews of the more limited European evidence can be found in Goddard et al. (2001) and Molyneux et al. (1997).

The important conclusion from most survey work is the considerable instability of results across individual studies, both with respect to the estimated absolute levels of CE and PE as well as the relative efficiency ranking of individual financial institutions.[5] Varying efficiency scores can be due to three major differences: (i) assumptions of the production model underlying costs and/or profits, (ii) the sample selection, and/ or (iii) the empirical specification of the efficient frontier. In this paper we focus on the effect of alternative specifications that accommodate heterogeneity on the stability of efficiency scores keeping sample and production model constant. Beforehand, we review some of the more important choices within all three dimensions and explain why it is implausible to expect that differences merely reflect alternative samples. To do so, we review German efficiency studies that use similar samples in terms of size, time, banking type and/or region with particular emphasis on the various methodological choices.

Most bank efficiency studies – both for Germany and in general – opt for some sort of parametric method. As mentioned earlier, among the most established approaches is stochastic frontier analysis (SFA), introduced by Aigner et al. (1977), Battese and Corra (1977) and Meeusen and van den Broek (1977), which deliberately accounts for random noise. Coelli et al. (1998) argue that SFA thereby avoids confining random noise with inefficiencies. An alternative approach is to use non-parametric methods. These enjoy the advantage of not imposing a particular structure on the data a priori.[6] A major drawback of this approach, however, is that inefficiencies are lumped together with random noise, for example due to measurement error. According to Mountain and Thomas (1999), banking studies are particularly prone to such errors because measurement of prices based on accounting information is notoriously difficult. Furthermore, growing heterogeneity across banks due to increased deregulation (Molyneux et al. 1997) and increasing size differences among competing banks (Goddard et al. 2001) render a comparison relative to an identical benchmark particularly sensitive to outliers if we do not explicitly account for random error and model sources of heterogeneity.

We therefore limit ourselves to parametric efficiency measurement. Table 1 depicts the four parametric studies using some form of stochastic frontier analysis

[5] As an illustration, consider CE and PE scores reported for Germany relative to a stochastic European frontier in Williams (2004), Bos and Schmiedel (2003) and Maudos et al. (2002). Mean CE ranges across studies between 81 and 91 percent. On the profit side differences are even stronger between 24 to 80 percent.

[6] Ali and Seiford (1993) provide a synopsis of the development of this approach.

that are available for German banking: Altunbas et al. (2001) and Lang and Welzel (1996, 1998a and 1998b).[7] For these studies, we introduce and discuss some choices based on the three above dimensions that can explain why efficiency scores differ so much in these studies.

Table 1: Overview German Efficiency Studies

	Altunbas et al. (2001)	LW (1996)	LW(1998b)	LW (1998a)
Model				
Profit	21%$^{1)}$ / 22%$^{2)}$	not estimated	not estimated	not estimated
Cost	16%$^{1)}$ / 13%$^{2)}$	15% - 50%	12%	8%
Sample				
Year(s)	1989-1996	1989-1992	1992	1989-1997
Observations	7,539	757	1,548	6,731
Region(s)	Germany	Bavaria	Germany	Bavaria
Group(s)	Bank type	10 size classes	9 size classes	
Banks	Cooperatives	Cooperatives	Cooperatives	Cooperatives
	Savings		Savings	
	Commercial		Commercial	
Control(s)	Equity	Branches	Branches	Branches
Specification				
Frontier	SFA$^{1)}$ / DFA$^{2)}$	SFA$^{1)}$	TFA$^{3)}$	SFA$^{1)}$
Function	Fourier	Translog	Translog	Translog
Technology	Time trend	Time trend	Asset growth	Time trend
Efficiency	Half-normal	Half-normal	n.a.	Half-normal
Truncation	at 0	at 0	n.a.	at 0
Estimator	Pooled CS	RE & FE panel$^{4)}$	Yearly CS	Pooled CS

$^{1)}$ Stochastic frontier analysis; $^{2)}$ Distribution free analysis; $^{3)}$ Thick frontier analysis;
$^{4)}$ Random and fixed effects panel estimators, respectively.

First, consider the modeling dimension. All German studies use the intermediation approach to model production. CE is analyzed significantly more often than PE. Altunbas et al. (2001) are the only ones who examine the profit dimension for German banks, too. This phenomenon holds not just for Germany but for bank efficiency analyses in general. Only recently, more interest in PE emerged. Cost inefficiency differences are considerable, ranging between 8 and 50 percent.

In the second panel in table 1, the sample characteristics used in the four studies are depicted. They underpin the argument that a comparison of efficiency across studies is hardly possible given sample differences. Even when comparing only German country studies, sample size, type of banks included and periods covered differ sometimes considerably. Note, however, that even for the two studies seemingly most alike, namely Altunbas et al. (2001) and Lang and Welzel

[7] Only one non-parametric study by Hauner (2004) exists on large German (and Austrian) banks.

(1998b), mean cost inefficiency in the former is around twice as high as in the latter.

Alternative choices in the third dimension, namely the empirical specification, might be responsible for this finding. We therefore discuss the more important specification choices encountered in the literature. Altunbas et al. (2001) employ the Fourier flexible functional form, while all studies by Lang and Welzel utilize the multi-input and -output translog functional form (Hasenkamp 1976). In fact, the majority of bank SFA studies employ the latter. Swank (1996) compares these functional forms. He concludes that the difference between the translog and Fourier flexible form appears to be negligible. Work by Berger and Mester (1997) confirms the finding.

Similarly, little variation exists in the treatment of technological change. Three out of four studies use a time trend to model technological change as a shift of the frontier over time in the vein of Baltagi and Griffin (1988).

Concerning the inefficiency component in total regression error, the assumption of a half-normal distribution is the most widely applied in the literature and also in the sample of German banking studies shown in table 1.[8] In view of these and other studies, Greene (1993) concludes that the half-normal distribution has the greatest appeal due to its ease of implementation and the abundant availability of ancillary calculations to draw inferences.[9]

Pooled cross-sections are common. Schmidt and Sickles (1984) argue that a cross-sectional estimator may bias results since the variance of expected inefficiency conditional on the total error never becomes zero, even if an infinite number of firms is added to the cross section. The intuition is that repeated observations for a single bank over time contain different information than a similar number of observations for separate banks. Kumbhakar and Lovell (2000) note that the advantage of panel estimators may be overstated, as most studies only have panel data of limited length at their disposal.

Overall, the evidence in table 1 suggests that the magnitude of cost inefficiency varies substantially, even in a comparison of studies that appear to be quite similar. From the available information, the ultimate determinants of the observed differences are difficult to pin down. We hypothesize that heterogeneity across banking sectors, regions, and size classes is one of the more prominent candidates causing the apparent instability across individual studies. We therefore turn next to the methodology required to account more explicitly for heterogeneity.

[8] Alternatives are the exponential, the Weibull and the Gamma distribution. Greene (1990) presents results for all four and finds that distributional assumptions alone do not have much impact on differences in efficiency.

[9] However, Battese points out in Coelli et al. (1998) that any a priori distributional assumption lacks a theoretical foundation.

3 Methodology

We begin by outlining a simple benchmark cost model for banks on the basis of the intermediation approach. Since the alternative profit model of Humphrey and Pulley (1997) differs only in a few respects, to conserve space, we introduce it via footnotes. We then discuss the role of heterogeneity, introduce three alternative specifications, and compare each to the benchmark specification. Finally, we introduce the empirical specification used.

3.1 Basic model

We follow the intermediation approach of Sealy and Lindley (1977) to model bank production. The main task of a bank is to channel funds from savers to investors. Therefore, the monetary volume intermediated is considered as output vector y. We assume that banks face perfect competition in input markets and are therefore price-takers when demanding inputs x. Thus, the bank faces a vector of exogenous input prices w. In transforming inputs into outputs we account for the role of equity, z, as an alternative to finance outputs (Hughes and Mester 1993).[10] The transformation function of the banking firm is depicted by $T(y, x, z)$. As the dependent variable we employ total operating cost, TOC, for the cost minimization problem and profits before tax, PBT, in the alternative profit maximization problem. To produce a given vector of outputs y, banks minimize cost by choosing input quantities x at given input prices, w. Using these definitions, the cost minimization problem is written as:

$$TOC(y, w) = \min_{x} \Sigma(w * x) \quad (1)$$
$$\text{s.t. } T(y, x, z) \leq 0$$

The Lagrangian of this constrained optimization is written as:

$$L = \Sigma(w * x) - \lambda T(\cdot). \quad (2)$$

We take partial derivatives with respect to each input x and the multiplier λ. Setting all of these equal to zero and simultaneously solving for x results in optimal input demand functions, $x^*(y, w, z)$, which in this model are also conditional on the available level of equity z.[11] The minimum cost level is then obtained by substituting the optimal input demand functions into the total cost function given

[10] Note that alternative capital structures already account for some heterogeneity.

[11] The maximization problem in the alternative profit model yields in addition optimal output prices $p^*(y, w, z)$.

by equation (1) to obtain:[12]

$$TOC^* = \Sigma(w * x(y, w, z)) = TOC^*(y, w, z). \tag{3}$$

Equation (3) is the minimum cost function and serves as the benchmark relative to which all banks are compared. Deviations from optimal cost can be due to two reasons: (i) random noise and (ii) suboptimal employment of inputs at given prices. We therefore write equation (3) as a stochastic frontier for a bank k in logs and add a composed error term ε to the deterministic kernel $f(y_k, w_k, z_k; \mathbf{b})$ leading to:

$$\ln TOC_k = f(y_k, w_k, z_k; \mathbf{b}) + \varepsilon_k, \tag{4}$$

where $\mathbf{b}$ is a vector of parameters to be estimated. The total error in equation (4) is depicted as $\varepsilon_k = v_k + u_k$, where v_k denotes random noise and u_k stands for deviations due to inefficiency. In the case of a cost frontier, inefficient input use entails higher than optimal cost and therefore u_k is strictly positive.[13] We need to specify a functional form for the deterministic kernel. Following the literature, we choose the multi-output translog functional form. In all four specifications the random error term v_k is assumed *i.i.d.* with $v_k \sim N(0, \sigma_v^2)$ and following Stevenson (1980) independent of the explanatory variables. The distribution of the inefficiency term u_k is i.i.d. $N|(\mu, \sigma_u^2)|$ in the benchmark model. It differs across specifications as shown in table 2 and is independent of the v_k. The reduced form of the benchmark specification can now be written in logs as:[14]

$$\begin{aligned}
\ln TOC_k(w, y, z) \quad = \quad & \alpha_0 + \sum_i \alpha_i \ln w_{ik} + \sum_m \beta_m \ln y_{mk} \\
& + \frac{1}{2} \sum_i \sum_j \alpha_{ij} \ln w_{ik} \ln w_{jk} + \sum_i \sum_m \gamma_{im} \ln w_{ik} \ln y_{mk} \\
& + \frac{1}{2} \sum_m \sum_n \beta_{mn} \ln y_{mk} \ln y_{nk} + \delta_0 \ln z_k + \frac{1}{2} \delta_1 (\ln z_k)^2 \\
& + \sum_i \omega_i \ln w_{ik} \ln z_k + \sum_m \zeta_m \ln y_{mk} \ln z_k + \eta_0 t + \frac{1}{2} \eta_1 (t)^2 \\
& + \sum_i \kappa_i \ln w_{ik} t + \sum_m \tau_m \ln y_{mk} t + \delta_2 \ln z_k t + \varepsilon_k.
\end{aligned} \tag{5}$$

[12]The alternative profit model assumes pricing power on the output side subject to a pricing opportunity set $H(p, y, w, z)$, where p denotes output prices. $H(\bullet)$ is another constraint next to $T(\bullet)$. Maximum profits $\pi^*(y, w, z)$ depend on given input prices, available equity and output quantities.

[13]In the profit frontier the total error is $\varepsilon_k = v_k - u_k$.

[14]We use maximum likelihood estimation to obtain both parameter estimates for equation (5) and the error components. We impose homogeneity of degree one in input prices and symmetry as, for example, in Lang and Welzel (1996).

Here outputs y, input prices w, control variable z (equity) are defined as previously. A time trend t captures technological change in the vein of Baltagi and Griffin (1988).

After imposing homogeneity of degree one in input prices and symmetry as in Lang and Welzel (1996), we estimate all models using the three-step procedure outlined in Kumbhakar and Lovell (2000). In step one, we estimate the reduced form with ordinary least squares (OLS). OLS provides a check whether the assumption that inefficiency exists is adequate (Waldmann 1982). In the case of no inefficiency, the total error ε consists solely of white noise. By contrast, under the existence of inefficiency, the u_k's are positive and therefore the distribution of total error $f(\varepsilon)$ is positively skewed. In step two, we derive the log-likelihood function for which we refer to Kumbhakar and Lovell (2000). The resulting log-likelihood function is maximized using a quasi-Newton method developed by Broyden, Fletcher, Goldfarb and Shanno (Judd 1999). In the algorithm, the Hessian matrix is replaced with an approximation that is positive semi-definite and updated at each iteration in the maximization process. Finally, we extract the expected value of the inefficiency term from its conditional distribution. We follow Jondrow et al. (1982) and use the conditional distribution of u given ε. A point estimator of technical efficiency is given by $E(u_k|\varepsilon_k)$, i.e. the mean of u_k given ε_k. Estimates of bank-specific cost efficiency are obtained by calculating:

$$CE_k = [\exp(-u_k)]^{-1}. \tag{6}$$

Cost efficiency equals one for a fully efficient bank that operates on the efficient frontier corrected for random noise. In the estimation of all specifications discussed in this section, we always take the intermediation approach, choose the parametric SFA approach, use the translog function for the deterministic kernel, use time trend variables to capture technological progress, and opt for normal error distributions. In all cases, a cross-section estimator is used. These choices reflect the consensus in the literature as reviewed above.

3.2 Accounting for Heterogeneity

A crucial characteristic of our benchmark model is the fact that all banks included in our analysis are assumed to use the same transformation function to convert inputs to outputs and thereby minimize costs. This transformation function represents the production technology that, together with the assumption of optimizing behavior under perfect competition, determines the efficient frontier.

Put differently, we assume that the shape of the frontier is the same for all banks.[15]

Our sample, however, may in practice be quite heterogeneous. Hackethal (2004) notes a number of examples. German savings banks differ from other banks due to funding advantages as a consequence of governmental guarantees. Additional sources of heterogeneity include alternative deposit insurance schemes in the respective banking sectors and regulation limiting the regional scope of operations. These systematic differences can have two effects on the stochastic frontier. First, they can result in parallel shifts of the frontier. Second, they can result in systematic deviations from the frontier.[16] The question of whether such a vector of exogenous factors h_k should be modeled to influence the position of the frontier versus the ability of management to attain that frontier was first recognized by Deprins and Simar (1989). Kumhakar and Lovell (2000) observe that:

> "In most cases, however, it is not obvious whether an exogenous variable is a characteristic of production technology or a determinant of productive efficiency. This is frequently a judgment call."

In our effort to make this judgement call, we use dummy variables h_k for different banking groups, regions of origin, and bank size to capture systematic differences across banks in our sample. In principle, we can use this vector h_k to appropriately account for heterogeneity in two ways. The first approach is to include h_k in the deterministic kernel of the frontier. For different groups specified according to dummies, the frontier is then shifted parallel. In the second approach, one specifies heterogeneity to influence the distribution of deviations from full efficiency. Then, the deviations u that capture a bank's ability to attain the frontier differ according to the groups determined by our dummy variables h_k. In either case, omission of relevant factors that influence operating cost can lead to biased efficiency scores.[17]

For a more precise discussion of the various options, consider first the benchmark specification under the assumption of homogeneity that ignores environmental factors h_k. In that case, the baseline cost frontier to estimate is $\ln TOC_k =$

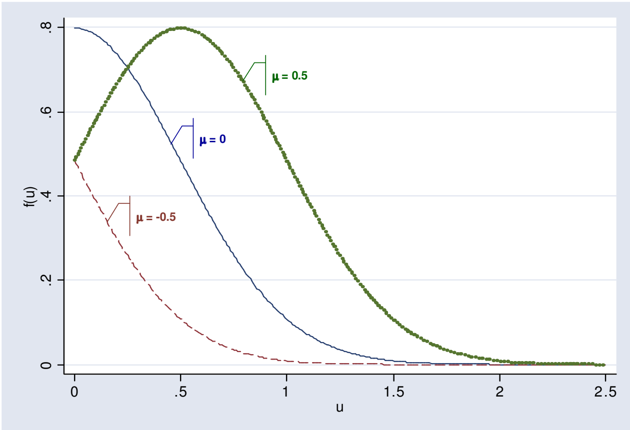
[15] Alternatively, it is possible to relax the assumption of a common transformation function. Battese et al. (2004) suggest enveloping single frontiers in a second stage analysis with a so-called *metafrontier*. An application to banking is provided by Bos and Schmiedel (2003), who estimate country specific frontiers and subsequently envelop these frontiers with a European metafrontier.

[16] Note that we assume for both approaches that factors accounting for heterogeneity, h_k, are orthogonal to efficiency.

[17] Our choice of indicators contained in h_k follows evidence from the literature. However, we caution that this choice may still fail to grasp the entirety of factors explaining banks' costs. Given the virtually infinite amount of further control variables we cannot rule out an ommitted variable bias.

$f(y_k, w_k, z_k; \mathbf{b}) + \varepsilon_k$, as in equation (4). The error consists of two components: the random term around the frontier v_k, and the asymmetric (non-negative) inefficiency error u_k. These are assumed to be *i.i.d.* with $v_k \sim N(0, \sigma_v^2)$ and $u_k \sim N|(0, \sigma_u^2)|$, respectively. Figure 1 illustrates the distribution of u for a constant standard deviation and three different means. Note that by assuming a truncated (half-normal) distribution with mean zero, we implicitly assume that the probability mass of the inefficiency distribution is concentrated close to the border. This implies that most banks are closely located to the frontier and only suffer from a relatively small amount of (managerial) inefficiency.

Figure 1: Truncated normal distributions of u for three alternative μ



In fact, there is no theoretical reason to make the ex ante assumption that the mean of the truncated half normal is zero. As plotted in figure 1, it could be negative as well as positive. A minor extension of the benchmark specification is to estimate the mean μ of the truncated half normal distribution from the data (Stevenson 1980). Interestingly, while maintaining the homogeneity assumptions with respect both to the deterministic kernel and the error distribution, allowing μ to be non-zero increases the ability to cope with hidden heterogeneity. To the extent that heterogeneity does play a role, it can now influence the location of the distribution of measured inefficiencies. We refer to this approach as the truncated model. An important limitation is the rather restrictive way how heterogeneity influences inefficiencies. We still neglect bank-specific sources of heterogeneity. In fact, estimation of a truncation point common to all banks may not suffice to grasp the variety of reasons that cause efficiency measures to differ so much.

The first way to account more explicitly for heterogeneity is to directly include the vector of environmental variables, h_k, in the deterministic kernel of the frontier. This implies for different banks or banking groups shifts of the efficient frontier. In contrast, the assumptions regarding the distribution of random deviations v and inefficiency u remain untouched. Hence, we estimate:

$$\ln TOC_k = f(y_k, w_k, z_k, h_k; \mathbf{b}, \mathbf{d}) + v_k + u_k, \tag{7}$$

where $\mathbf{d}$ is an additional vector of parameters in the deterministic kernel accounting for systematic differences across banks due to region, size and banking type. We assume that the additional dummy variables remedy an omitted variable bias present in equation (4). Therefore, equation (7) represents a more accurate specification of the cost function and will yield more accurate measures of (in)efficiency scores. Because we do not include interaction terms of dummy variables and other production variables, we also assume that the shape of the frontier is identical for all banks. Thereby, we maintain the assumption that the transformation function, for example with respect to scale and scope economies, is the same for all banks. In sum, we allow the *position* of the frontier to be different for various (groups of) banks.

By contrast, the second approach assumes that heterogeneity dummies h_k shift the distribution of inefficiency, while the frontier $f(y_k, w_k, z_k; \mathbf{b})$ is the same for all banks, just as in both the benchmark and the truncated model. The difference is that each firm's u_k now depends on h_k. This implies a shift of the inefficiency distribution similar to figure 1. But in extension to the truncated model, the distribution now takes into account the omitted variable bias as in the kernel approach. That is, we focus on the impact of exogenous factors on a bank's ability to attain the frontier, rather than the group-specific position of the frontier. Conceptually, it is important to note that the environmental factors assumed to influence the inefficiency term can be beyond the control of management. That is, the interpretation of measured inefficiency needs to be broadened to include both managerial inefficiency and inefficiency due to external factors that prevent a bank's management from reaching the frontier.

Empirically, we follow in the latter case Kumbhakar et al. (1991), who suggest a single-stage approach to allow exogenous factors h_k to determine the mean of the inefficiency term's density function.[18] It implies that the (homogeneous) cost frontier in equation (4) is estimated with different distributional assumptions on the inefficiency error. The inefficiency error then is *i.i.d.* and drawn from the truncated distribution $u_k \sim N|[(\mu + \mathbf{d}'h_k), \sigma_u^2]|$. An important implication is that we can account for heterogeneity across banks and still benchmark all (different)

[18] The alternative is a two-stage approach. In the first stage, equation (4) is estimated under the (implicit) assumption of homogeneity. In the second step, a set of environmental variables is regressed on estimated (in)efficiency. For a discussion of the drawbacks of this approach see Greene (2003) and Kumbhakar and Lovell (2000).

banks against an identical frontier. In doing so, the distribution and hence the ability of banks to achieve full efficiency now depends on h_k.

Currently, no decision criterion is available to our knowledge to determine whether heterogeneity is important in empirical efficiency analysis, nor to what extent heterogeneity depends on the sample of banks. Moreover, under the assumption that heterogeneity matters, it is unclear whether it is better to cope with heterogeneity through inclusion of additional exogenous variables in the deterministic kernel or through modelling the inefficiency error differently.

In the remainder of this paper, we estimate cost and profit efficiency for a common sample of German banks and a common sample period with four different specifications: (i) the simple baseline specification; (ii) the baseline specification with the mean of the truncated half normal at μ; (iii) with environmental variables in the deterministic kernel; (iv) and with environmental factors in the distribution of the inefficiency term (i.e. the heterogeneity in error specification). We want to find out exactly how the results differ as a consequence of opting for a different specification. To this end, we turn next to the four respective empirical specifications to consider heterogeneity. We refer to Kumbhakar and Lovell (2000) with respect to the consequences for the likelihood function.

The different assumptions regarding the deterministic kernel and the mean of the error distribution for these four specifications are summarized in table 2.

Table 2: Deterministic kernel and error assumptions across models

Specification	Kernel f($\cdot$)	Inefficiency u
1. Benchmark	f(y_k,w_k,z_k;b)	$u_k \sim N\|(0, \sigma_u^2)\|$
2. Truncated	f(y_k,w_k,z_k;b)	$u_k \sim N\|(\mu, \sigma_u^2)\|$
3. Kernel	f(y_k,w_k,z_k,h_k;b,d)	$u_k \sim N\|(\mu, \sigma_u^2)\|$
4. Error	f(y_k,w_k,z_k;b)	$u_k \sim N\|(\mu + dh_k, \sigma_u^2)\|$

The specification of the deterministic kernel for the truncated and the error model is identical to the benchmark model in equation (5). Changes are limited to the assumptions concerning the inefficiency distribution. In contrast, the reduced form of the heterogeneity in kernel specification requires an extension of equation (5) with our dummy variables h_k leading to:

$$\ln TOC_k(w, y, z) = [\text{equation 5}] + \sum_g d_g h_{gk}, \tag{8}$$

where g indexes groups for which we specify dummies.

To assess the importance of accounting for heterogeneity, we subsequently compare cost and profit frontier estimates as well as efficiency levels and rankings across specifications. Before turning to our results, we first dicuss our data.

4 Data

In this paper we build on the premise that all banks included in our analysis have access to the same technology and production factors to produce loans and other financial services. Because of similar customers, institutional set-up with local and apex institutes, and akin product portfolios, we believe this is a plausible assumption for cooperatives and savings banks. We therefore exclude commercial banks which require, in our view, an explicit incorporation of different risk profiles, given this banking group's focus on wholesale and investment banking activities. Consequently, we can assess the impact of different modeling choices accounting for heterogeneity on a fairly homogenous sample consisting of two banking groups that jointly account for approximately 35 percent of total assets in Germany's three banking pillars. We use balance sheet as well as profit and loss account data for all German savings and cooperative banks that reported to the Deutsche Bundesbank between 1993 and 2003.

Table 3: Descriptive statistics on SFA variables employed

Variable		Mean	SD	Min	Max	N
y_1 1)	Interbank loans	49.9	146.5	0.001	4,360	30,374
y_2 1)	Customer loans	286.9	743.9	0.670	22,600	30,374
y_3 1)	Securities	118.3	293.3	0.003	6,570	30,374
w_1 2)	Price of fixed assets	16.5	110.5	0.744	14,062	30,374
w_2 3)	Price of labour	49.7	107.7	0.377	18,400	30,374
w_3 2)	Price of borrowed funds	3.8	0.8	0.952	8.2	30,374
z 1)	Equity	21.4	53.4	0.175	2,060	30,374
TOC 1)	Total operating cost	28.0	66.3	0.175	1,873	30,374
PBT 1)	Profit before tax	5.2	13.4	-35.91	417	30,374

1) Measured in millions of Euros; 2) Measured in percent;
3) Measured in thousands of Euros.

Table 3 gives descriptive statistics for input prices, output quantities, equity, and dependent variables. The outputs are interbank loans y_1, commercial loans y_2, and securities y_3. A bank uses three production factors to produce outputs: fixed assets x_1, labor x_2, and total borrowed funds x_3. We follow the literature and approximate the price of fixed assets w_1 by dividing depreciation and other expenditures on fixed assets over the volume of fixed assets. The price of labor is calculated as an average wage rate w_2 by relating the Euro amount of personnel expenses to the number of full time equivalent employees (FTE). We approximate the price of borrowed funds w_3 by dividing interest expenses over total borrowed funds.[19]

An important characteristic that emerges from table 3 is the presence of negative profits. In the translog specification, one runs into the problem that the log of negative numbers is not defined. In the literature, different solutions exist. One solution is to delete these observations. Another solution is to add the minimum profit (i.e. the maximum loss in the sample) plus one to each bank's profits before taking logs. Both of these approaches can bias results and we argue that an alternative transformation should generally be employed.[20] To avoid negative numbers, we construct a negative profit indicator variable, NPI, as an additional right-hand side variable. For banks that exhibit positive profits, this variable has a value of one. However, for banks exhibiting negative profits, we substitute the left-hand-side, PBT, with a value of one. On the right-hand side, we include the absolute value of negative profits as the NPI variable.[21]

As discussed in section 3, we specify dummy variables for different banking groups, regions, and bank sizes to either shift the frontier or shift the distribution of deviations from it.[22] We distinguish 8 banking groups in total, namely 2 types of savings banks and 6 types of cooperative banks. Regions are defined as the 16 states (*"Bundesländer"*) of the Federal Republic of Germany. On the basis of total assets we allocate banks to four equally distributed size classes.[23]

To determine if the heterogeneity among banks is significant, we conduct a Kruskall-Wallis test (see Kruskall and Wallis 1952). According test statistics are shown in table 4. The null hypothesis is that several samples are drawn from the same population.[24] With the exception of the price of fixed assets compared across size classes, we reject the hypothesis that the variable means are the same across different groups.

[19] We estimated all models excluding extreme outliers at alternative cutoff points akin to Maudos et al. (2002). Results were robust.

[20] In our sample there are 331 observations with negative profits.

[21] For an in-depth discussion of this approach we refer to Bos and Koetter (2005).

[22] Mean values for all SFA variables per region, banking group, and size class confirm that substantial differences exist among banks in Germany. Descriptive statistics are not reported per group to conserve space. Data are available upon request.

[23] We distinguish public savings, independent savings, cooperative banks (commercial), cooperative banks (rural), Sparda banks, PSD banks (*"Post-, Spar- und Darlehensvereine"*), civil servant's banks and Raiffeisen banks. These groups resemble the taxonomy of the Bundesbank. Size class boundaries in millions of Euros: Size I < 65 ; $65 \leq$ Size II < 153 ; $153 \leq$ Size III $<$ 435 ; $435 \geq$ Size IV.

[24] We also conducted independent sample t-tests for east versus west banks as well as cooperative versus savings banks. Results confirmed that differences in means between the two respective sub-samples are significantly different from zero.

Table 4: Kruskall-Wallis test for heterogeneity of SFA variables

	Region (15)	Group (7)	Size (3)
y_1	2,482.3	13,244.5	20,396.1
y_2	1,195.1	17,734.8	27,605.0
y_3	2,229.0	17,967.4	24,980.6
w_1	2,638.3	287.0	*5.7*
w_2	5,089.1	11,55.7	95.2
w_3	3,241.7	357.5	48.6
z	1,484.8	17,778.6	27,578.4
TOC	1,577.1	18,885.2	28,124.2
PBT	1,674.9	17,444.4	24,781.3

Degrees of freedom between brackets; italics indicate that the difference is not significant at the 10% level.

5 Results

In this section we first discuss parameter estimates for the four cost and profit frontiers, respectively. Second, we compare efficiency scores to quantify the impact of different approaches to accommodate heterogeneity. Third, we elaborate on the influence of alternative specifications on efficiency rankings.

5.1 Frontier Estimates

We estimate all four specifications listed in table 2 and report parameter estimates in the appendix. Across all four specifications and for both cost and profit frontiers, parameter estimates of input prices, output quantities, and interaction terms are significantly different from zero. The additional parameters capturing heterogeneous environments in the deterministic kernel or in the error are also highly significant for the most part. However, due to numerous interaction effects, inference from individual parameters is difficult. Therefore, we abstain from the interpretation of single coefficients.[25] Instead, we focus on the parameters that determine the shape and location of the efficiency distribution, including total variance σ; the ratio of variance of the (truncated) inefficiency distribution σ_u to the variance of the random error σ_v which is depicted by λ, and the parameters accounting for heterogeneity μ and $\mathbf{d}$.

Parameters σ and λ are significant in the baseline half normal specification in the cost (table 8) and profit (table 9) models. For the profit frontier σ is higher than in the case of the cost frontier. Also, the share attributable to inefficiency relative to random noise λ is larger for the profit model. These results indicate

[25] Note that the coefficient for NPI is significantly different from zero in all specifications. In the cost case, this control variable exhibits a positive sign. This implies that positive values (i.e., banks suffering from losses) are related to higher cost.

that systematic deviations from the profit frontier are higher compared to the cost case.

Results for the truncated specification are puzzling at first sight. On the one hand, estimates of σ, λ, and μ are individually not significant for either the cost or the profit frontier. On the other hand, the log-likelihood value for the truncated specification is higher compared to the baseline specification with truncation at zero.[26] Rejecting the hypothesis of a composed error in the truncated specification by finding an insignificant λ could imply that inefficiency does not prevail among German banks. If so, SFA is an inappropriate specification of the cost model. At the same time a log-likelihood ratio test of the benchmark specification versus OLS suggests that the average response function is inferior to SFA. Therefore, we conclude that the simplest strategy to allow for heterogeneity by means of a uniform truncation point does not suffice to capture all differences across banks that influence efficiency. Intuitively, while we may have problems estimating a significant location parameter μ, modelling the benchmark without it is inferior. We thus need to accommodate heterogeneity in a more detailed fashion.

Therefore, we consider next the heterogeneity in kernel specification. We provide parameter estimates in columns six and seven of tables 8 and 9 in the appendix. Most heterogeneity parameter estimates are significant in both cost and profit frontiers. As an improvement relative to the truncated specification, the parameter estimates for σ and λ in the cost model are significant. However, for the profit case, σ and λ are only barely significant at the 10 percent level. For both cost and profit frontier specifications, the magnitude of the variance parameter σ is larger compared to the baseline specification. At the same time the share of deviations due to inefficiency relative to random noise λ is higher. Moreover, the estimate for a common location parameter μ is also insignificant. Since the truncated error and the kernel specifications are nested, we can formally test whether $\mathbf{d} = 0$ and find that we can reject the truncated specification. Thus, the heterogeneity in kernel specification highlights the importance to account explicitly for exogenous factors. However, reservations persist concerning the appropriateness of the specification on grounds of an insignificant truncation point μ in both the cost and profit case.

Next, we consider the heterogeneity in error specification. Compared to the kernel specification, this specification allows us to assess the relevance of environmental factors in influencing management's ability to attain full efficiency. For both frontiers, we find that the parameters σ and λ are significant at a restrictive confidence level of 1 percent. For the profit frontier, this is an improvement

[26](Unreported) results from a log-likelihood ratio test for the hypothesis that $\mu = 0$ also confirm that the truncated model is preferred to the baseline model.

compared to the heterogeneity in kernel specification. As a second improvement, the location parameter of the inefficiency distribution μ is now clearly significant for both frontiers. At the same time, the number of insignificant parameters for the deterministic kernel $\mathbf{b}$ is substantially higher in the kernel cost specification compared to the heterogeneity in error specification. This also holds to a lesser degree for the profit frontier. Regarding estimated environmental parameters $\mathbf{d}$ we find that both heterogeneity specifications hardly differ as far as the number of (in)significant parameter estimates is concerned. Nonetheless the overall fit of the kernel specification appears to be better, as evidenced by a somewhat higher likelihood value for both the cost and the profit frontier. Note, however, that we cannot compare the two specifications directly with each other as they are not nested.

This result is cumbersome because (as we noted previously) no theoretical argument exists favoring one approach over the other. Our empirical results also fail to provide a univocal judgement. Therefore, we only dare to draw two tentative conclusions. First, the improved significance of critical parameters σ, λ, and μ in the error specification provides some evidence in favor of the approach to model heterogeneity in the error. On the other hand, the information criteria of the log-likelihood lend more credit to the kernel specification. Second, specifying heterogeneity in the error allows us to explain the sources of inefficiency. In our view it is not only appealing to know that accounting for geographical origin matters in efficiency measurement, but also (for example) which state has a positive or negative effect on the location of the inefficiency distribution.[27]

In sum, we find that heterogeneity significantly influences stochastic cost and profit frontiers and should therefore be included in (bank) efficiency studies. The baseline and heterogeneity in error specification produce sensible results, whereas the truncated specifications (with or without exogenous indicator variables in the deterministic kernel) suffer from difficulties when estimating location parameters of the inefficiency distribution. Because efficiency scores crucially hinge on heterogeneity, we turn next to a comparison of efficiency scores across specifications.

[27] As a caveat note that a positive coefficient of $\mathbf{d}$ in the (cost) error specification does not necessarily imply higher (cost) inefficiency. This is because the latter depends on the starting point of both the combined and the truncated error distribution. To evaluate the effect of single coefficients in the heterogeneity in mean model, one can follow Kumbhakar and Lovell (2000) and calculate the derivative of the conditional inefficiency distribution with respect to the heterogeneity variable h_k, i.e. $[\partial E(u_k|\varepsilon_k)/\partial h_{ik}]$.

5.2 Efficiency Levels

In table 5 we provide descriptive statistics for CE and PE. Two conclusions are obvious. First, in all specifications we can confirm previous findings that CE is higher than PE. The difference between mean PE and CE varies depending on specifications and ranges between 8 (for the truncated specification) and 26 (for the half normal specification) percentage points.

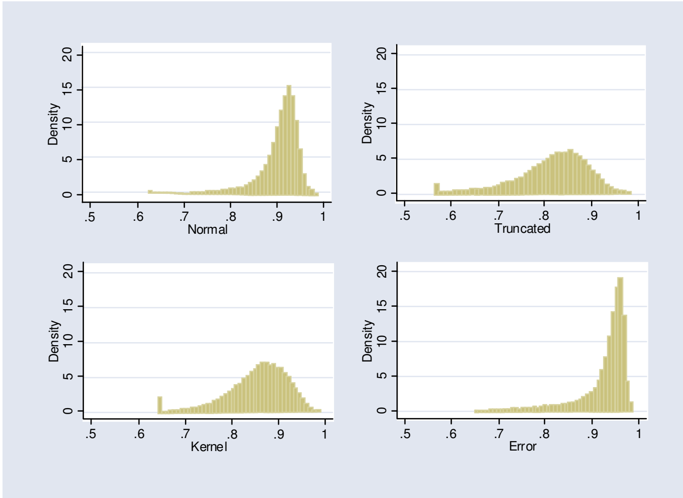
Table 5: Comparison of descriptive statistics efficiency levels

Specification	Half normal		Truncated		Kernel		Error	
	1		2		3		4	
Efficiency	Cost	Profit	Cost	Profit	Cost	Profit	Cost	Profit
Mean	0.906	0.648	0.815	0.732	0.853	0.736	0.920	0.707
SD	0.042	0.158	0.079	0.158	0.066	0.158	0.066	0.162
Skewness	-2.027	-0.534	-0.906	-1.357	-0.932	-1.271	-2.190	-1.152
Kurtosis	9.577	0.967	3.857	0.961	3.941	0.965	7.670	0.962
Min	0.625	0.291	0.566	0.237	0.642	0.268	0.647	0.237
Max	0.987	0.967	0.985	0.961	0.988	0.965	0.988	0.962

Second, the instability of cost and profit efficiency due to alternative treatments of heterogeneity is clearly illustrated since mean cost inefficiency ranges across specifications between 8 and 19 percent and foregone mean profits vary between 27 and 35 percent of optimal profits. We conclude that different specifications affect mean efficiency estimates considerably, even when holding all other specification choices constant and when using a fairly homogenous sample of banks. A closer investigation of the differences across specifications of CE and PE, respectively, seems warranted.

We begin with CE scores. Compared to the baseline half-normal specification, the truncated specification identifies additional waste due to poor input management on the order of 9 percent on average. Visual inspection of the "truncated" distribution of CE in figure 2 shows that it resembles a symmetric rather than a truncated distribution. This result, in conjunction with insignificant shape and location parameters σ and μ, suggests considerable "hidden" heterogeneity in the inefficiency estimates.

Figure 2: Distributions of estimated CE across models



In the cost kernel specification we consider additional environmental information h_k by including dummies on banking group, region and size in the efficient frontier. Mean CE improves compared to the truncated specification by approximately 4 percentage points. The intercept of the stochastic cost frontier shifts upward for those groups exhibiting positive dummy variables in the kernel. For example, parameter estimates of $\mathbf{d}$ for a civil servant bank operating in Saxony in size class two indicate higher stochastic cost. Intuitively, the costs of a bank in this group may be systematically higher because it operates under less buoyant economic conditions and faces higher unit costs for its inputs, given the relatively small size of the bank. When such reasons for systematic deviations from optimal costs are not taken into account, they are falsely identified as inefficiency.

In the baseline model $\mu = 0$ by assumption, which generally results in the majority of banks being located close to the efficient frontier (see figure 1). By contrast, a positive truncation parameter in the kernel specification normally leads to a higher expected value of the inefficiency distribution. This indicates that more banks now lie further below the efficient frontier. But we also find, that in both the truncated and the kernel specification, the location parameter μ is not significantly different from zero. Even so, CE in the kernel specification is around 5 percentage points lower than in the basic model. Furthermore, visual inspection of the CE distribution in figure 1 reveals that this specification leads again to a distribution much closer to normal than to half-normal. As in the truncated specification, this indicates persistent "hidden" heterogeneity that cannot be adequately grasped by a common truncation point of the inefficiency distribution.

Let us therefore turn now to our final approach: the error specification. We observe that most dummies influence the error distribution significantly. Consequently, we no longer estimate a single truncation point that is identical across banks but rather allow the mean of the truncated distribution to depend on a multitude of factors. A lower (and significant) estimate for μ compared to the truncated and kernel specification implies that the deviation from full efficiency is on average lower as u is more likely to be located closer to zero.

In comparison to the baseline specification, including dummies explains a lot of the deviation from the frontier, thereby identifying the latter as random noise rather than inefficiency. Mean CE exceeds the level found with the baseline half-normal specification by two percentage points. In addition, we also find that the skewness and kurtosis in table 5 do not raise concerns of the kind discussed for the truncated and kernel specification. Figure 2 further confirms that the distribution of CE measures is closest to a half-normal after directly accounting for heterogeneity in the inefficiency distribution. This suggests that the error specification can cope best with "hidden" heterogeneity. Together with significant shape and location parameters σ and μ, parameterization of half-normally distributed inefficiency scores seems most appropriate here.

In sum, it is clear that accounting for heterogeneity is necessary. But there is no reason to believe that either the kernel or the error specification yield efficiency results that are more correct than the other. After all, the true level of inefficiency cannot be observed. Unfortunately, clear cut preferences neither emerge from theoretical reasoning nor estimation results. While the former lacks a sound decision criteria, the latter suffers from mixed signals on the basis of information criteria and parameter estimates for kernel and error, respectively. On balance, we have a weak preference for the heterogeneity in error specification in the cost case. The reason for this preference rests on the distributional properties of CE exhibited by each specification and the significance of important parameters that determine the location and shape of the error distributions.

Turning to the profit results, estimated inefficiency of about 35 percent on average in the baseline specification is in line with previous findings in the literature. All three specifications that account for heterogeneity yield higher mean PE. Results are thus less mixed with regard to the effect of alternative specifications on mean PE compared to the baseline specification. We conclude that the choice of specification makes less of a difference in the profit case than in the cost case.[28]

[28] It could also occur if most of the regression error is due to assuming that banks have market power in output markets within the boundaries of a pricing opportunity set. If this is a poor specification in the first place, the effect of heterogeneity may be of too little importance to show up here. Consequently, specification of a perfect (output market) competition model including output prices is highly desirable. But since such data are unavailable, this approach is beyond the scope of this paper.

However, differences in mean PE of up to 8 percentage points relative to the baseline specification also imply that choosing one of the three approaches is imperative. To assess whether we can identify the best specification out of the three, we follow the same structure as for the cost case, but in a more condensed fashion to conserve space.

With respect to distributional indications in table 5, we note two issues. First, for any of the four profit specifications, the mass of banks is no longer located close to full efficiency. While negatively skewed, the distribution of inefficiency scores exhibits fat tails. Furthermore, the distribution for the baseline specification reflects properties of a truncated half-normal distribution the least. Second, the differences between the three alternative specifications are small as indicated by skewness and kurtosis, as well as mean efficiency scores. Therefore, we conclude with regard to alternative PE specification that accounting for heterogeneity is necessary as mean PE is around eight percentage points higher after doing so. Moreover, as opposed to the cost case, the differences across alternative specifications is small at 2.5 percentage points at most. However, on the basis of clearly significant estimates of critical parameters, we again weakly prefer the heterogeneity in error specification.

5.3 Efficiency Rankings

A major virtue of SFA is the ability to rank individual firms. Therefore, we are particularly keen to learn whether alternative specifications identify similar banks as best and worst in class, respectively. We therefore measure the rank order correlation between CE and PE with Spearman's ρ. An important finding is that CE and PE measure different kinds of managerial skill. As shown in the lower left corner of table 6, almost all correlation coefficients between CE and PE measures are significant and negative. We conclude that only few banks manage to be simultaneously efficient in handling their costs and profits, a result well in line with the literature.

Table 6: Rank order correlations across models

Efficiency	Specification	CE Normal	CE Truncated	CE Kernel	CE Error	PE Normal	PE Truncated	PE Kernel
CE	Truncated	0.994						
CE	Kernel	0.803	0.810					
CE	Error	0.880	0.908	0.757				
PE	Normal	-0.029	-0.022	0.070	*-0.001*			
PE	Truncated	-0.027	-0.018	0.073	*0.006*	0.999		
PE	Kernel	0.065	0.072	0.070	0.075	0.950	0.952	
PE	Error	-0.029	-0.017	0.074	0.017	0.994	0.996	0.949

Italics indicate correlations are not significant at the 10% level.

With respect to differences across specifications, table 6 further reveals that CE scores, in the upper left part of the table, are more strongly affected by alternative specifications than PE scores in the lower right part of the table. Regarding CE, the correlation between the baseline and truncated specification is the highest despite the largest difference in mean efficiency. This indicates that while levels of CE differ, the shift of the inefficiency distribution seems to affect all banks in the sample to a very similar degree. Thus, qualitative results in terms of which banks are top performers and which are potentially troubled are similar.

By contrast, the inclusion of additional factors in efficiency estimation leads to a substantial decline of rank order correlation to around 80 to 90 percent. The heterogeneity in kernel specification ranks a substantial portion of banks markedly differently. This need not be a problem if most re-rankings occur in the middle ranks because regulators are particularly interested in top and worst performers. Hence, we seek to shed light on the stability of rankings in the tails of the inefficiency distribution. We note beforehand that PE rankings are far less affected by (not) accounting for heterogeneity. Rank order correlation coefficients range between 95 and 99 percent in the profit case. Hence, the identification of potentially endangered banks as opposed to likely role-models is similar despite differences in mean PE.

Let us therefore consider the issue of identifying different banks as potentially endangered versus possible role-models on the basis of CE rankings. We do not use simple rank order correlation coefficients within one decile, as low correlation be due simply to minor changes in the order of rankings. For example, a bank could be ranked 5^{th} in the baseline specification and 50^{th} in the heterogeneity in error specification. This might already entail far below perfect rank order correlation within the top decile. But in terms of informational value, it would add little as both are certainly still in the top decile. Put differently, we are less interested in the exact rank of a single bank. Instead, we want to find out how many banks that are previously top performers are re-ranked as worst performers under alternative specifications and vice versa. Table 7 gives the result.

We use the error specification to investigate how many banks are re-ranked. In each of the three pairs of columns in table 7 we ask in which decile of the error specification's CE distribution are the best and worst performers located, according to the baseline, truncated, and kernel specifications?[29]

We first consider best performers in the top deciles. A comparison of the top decile according to the three specifications to the top decile of the heterogeneity in error approach indicates that 32% $(= (3,037-2,071)/3,037)$, 29%, and 41% of

[29] For example, out of 3,037 banks with the highest CE according to the baseline specification, 2,071 banks are also ranked as best CE performers in the error specification.

Table 7: CE rankings of best and worst practice banks across specifications

	Baseline		Truncated		Kernel	
Error specification decile	Top	Flop	Top	Flop	Top	Flop
1 (Flop)	0	2,262	1	2,377	17	1,656
2	0	500	0	480	20	353
3	1	140	0	119	24	277
4	3	67	3	31	21	189
5	6	26	4	20	33	178
6	20	17	9	5	43	156
7	57	13	42	2	94	118
8	176	4	147	3	270	69
9	703	8	670	1	708	38
10 (Top)	2,071	1	2,161	0	1,807	4
Total N	3,037	3,038	3,037	3,038	3,037	3,038

banks, respectively, are ranked differently in the latter specification. This result demonstrates that alternative specifications of efficient frontiers lead not only to different efficiency levels but also to different rankings. However, very few banks are re-ranked markedly different. Only around 9 former top banks according to the baseline and truncated specification, respectively, are re-located to the 5^{th} or worse decile by the error specification. Strikingly, only one bank identified as a top bank in the truncated specification is re-ranked by the error approach as a total flop.

This result implies that, despite imperfect correlation coefficients in table 6, top performers' efficiency levels and rankings do not differ a lot between the baseline, the truncated, and the heterogeneity in error specifications. With regard to the heterogeneity in kernel approach, the results in table 7 illustrate our concerns regarding full reliance on correlation coefficients. While the rank order correlation between the kernel and the error specification is 0.757, we find that 37 banks formerly ranked in the top decile according to the former are now located in the lowest two deciles of the latter. Apparently, some banks are particularly sensitive towards the specification of heterogeneity.

Consider next the re-distribution of flop performers across specifications. The comparison of worst performing banks of the three alternative specifications and their respective ranking in the error specification reveals that 26% $(= (3,038 - 2,262)/3,038)$, 22%, and 45% percent of flop performers are re-ranked, respectively. The number of different ranked banks according to the kernel and the error approach is thus higher. Perhaps even more important, we find that also in the normal and truncated specifications some banks identified previously as worst performers are oppositely identified as role models after accounting for heterogeneity in the error. As was previously the case, the number of banks that are drastically re-ranked in deciles nine and ten is highest in the comparison of the heterogeneity in kernel versus error specification. The number of banks identified as worst in class according to the baseline, truncated, and kernel specification, but re-ranked as role model banks in the error approach are 9, 1, and 42, respectively.

In sum, the most important criterion for observers of the industry is fairly robust: those banks that are top in one specification are also among the best in an alternative specification, and, vice versa. Opposite re-classification of just 0.15 percent of all observations between the error and kernel specifications in our view boosts confidence in the reliability of the efficiency scores. We conclude, however, that banks exhibiting strong rank sensitivity with regard to the treatment of heterogeneity deserve particular attention. If these institutions, in contrast to the vast majority of all other banks in the sample, cannot be equally well described by different approaches to heterogeneity, regulators and practitioners should investigate why these banks differ so much.

6 Conclusion

In this paper we investigate the influence of alternative approaches to account for heterogeneity on the robustness of efficiency measures estimated with stochastic frontier analysis. To isolate the role of heterogeneity, we introduce a benchmark specification and three alternative cost and profit frontiers. We compare each specification by selecting a common production set and using an identical sample of German cooperative and savings banks from 1993 to 2003. Our results lead us to five important conclusions.

First, accounting for heterogeneity matters. Even though our sample is fairly homogeneous, environmental indicators substantially enhance estimation results. Mean cost and profit efficiency levels differ considerably from the baseline specification when including simple indicator variables for banking types, regions, and size classes.

Second, especially CE results are heavily influenced by the specification of heterogeneity. Specifying heterogeneity in the kernel leads to mean CE that is approximately five percentage points lower than the basic model, while the error specification improves mean CE by approximately two percentage points. By contrast, any approach to control for heterogeneity in the profit specification leads to a higher mean PE within the range of five to eight percentage points.

Third, alternative specifications strongly affect the ranking of banks based on CE. Rank order correlation coefficients are lowest between the error and the kernel specifications. However, we find that, even in the two least correlated specifications (error versus kernel), only around 0.15 percent of former top (flop) performers are re-ranked as flop (top) performers. We conclude that efficiency estimates differ after accounting for heterogeneity but provide sufficiently stable information about extreme performers. Banks that exhibit high sensitivity in CE rankings depending on specifications should be investigated on a case-by-case basis to better understand why these banks are so different.

Fourth, our empirical results do not completely favor one approach to account for heterogeneity over the other (error versus kernel). This observation is consistent with Kumbhakar and Lovell (2000), who state that it remains largely a judgement call as how to account for heterogeneity. We develop for this sample a weak preference for the heterogeneity in error specification for two reasons. First, important parameters regarding the position and shape of the inefficiency distribution are insignificant in the kernel approach. Second, the distributional properties of estimated efficiency scores in the error approach indicate that this (and the normal-half normal) specification can cope adequately with the 'hidden' heterogeneity.

Fifth, independent of specification, we find that mean profit inefficiencies are quantitatively more important than foregone cost savings. Low and even negative correlations suggest that CE and PE measures capture different kinds of managerial skills. Thus, both dimensions should be measured.

Our overall conclusion is that efficiency studies in general and bank efficiency studies in particular should account for heterogeneity across sample firms. Especially when efficiency measures are employed for policy purposes, a careful choice of models and specifications is essential to be able to make inferences about managerial behavior.

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Appendix

Table 8: Parameter estimates cost frontier

COST	Half-normal		Truncated		Kernel		Error	
LL	19,571		20,143		26,914		24,796	
σ	0.163	0.000	1.638	0.624	1.192	0.000	0.223	0.000
λ	1.221	0.000	16.92	0.624	15.791	0.000	2.651	0.000
Iterations	9		84		107		223	
TLF [1)]	0.000001		0.00001		0.0001		0.000001	
TLG [2)]	0.000001		0.000001		0.000001		0.000001	
TLB [3)]	0.000001		0.000001		0.000001		0.000001	
Variable	b	p-value	b	p-value	b	p-value	b	p-value
Constant	-4.268	0.000	-4.335	0.000	-1.634	0.000	-1.634	0.000
$\ln y_1$	0.334	0.000	0.382	0.000	0.339	0.000	0.339	0.000
$\ln y_2$	0.442	0.000	0.444	0.000	0.210	0.000	0.210	0.000
$\ln y_3$	0.353	0.000	0.425	0.000	0.371	0.000	0.371	0.000
$\ln w_1$	0.205	0.000	0.110	0.000	0.025	0.122	0.025	0.898
$\ln w_2$	-0.383	0.000	-0.352	0.000	0.034	0.223	0.034	0.000
$\ln z$	0.060	0.191	-0.068	0.127	-0.042	0.243	-0.042	0.981
$\frac{1}{2}\ln y_1 \ln y_1$	-0.006	0.501	-0.074	0.000	-0.129	0.000	-0.129	0.000
$\frac{1}{2}\ln y_1 \ln y_2$	0.048	0.000	0.040	0.000	0.034	0.000	0.034	0.000
$\frac{1}{2}\ln y_1 \ln y_3$	-0.079	0.000	-0.091	0.000	-0.084	0.000	-0.084	0.000
$\frac{1}{2}\ln y_2 \ln y_2$	-0.037	0.000	-0.058	0.000	-0.075	0.000	-0.075	0.000
$\frac{1}{2}\ln y_2 \ln y_3$	0.119	0.000	0.104	0.000	0.116	0.000	0.116	0.000
$\frac{1}{2}\ln y_3 \ln y_3$	-0.125	0.000	-0.135	0.000	-0.145	0.000	-0.145	0.000
$\frac{1}{2}\ln w_1 \ln w_1$	0.061	0.000	0.054	0.000	0.042	0.000	0.042	0.000
$\frac{1}{2}\ln w_1 \ln w_2$	-0.033	0.000	-0.033	0.000	-0.022	0.000	-0.022	0.000
$\frac{1}{2}\ln w_2 \ln w_2$	0.062	0.000	0.107	0.000	0.106	0.000	0.106	0.000
$\frac{1}{2}\ln z^2$	-0.002	0.382	-0.029	0.000	-0.028	0.000	-0.028	0.000
$\ln y_1 \ln w_1$	0.015	0.000	0.020	0.000	0.002	0.094	0.002	0.002
$\ln y_1 \ln w_1$	0.003	0.235	0.001	0.628	0.002	0.412	0.002	0.000
$\ln y_1 \ln w_1$	-0.090	0.000	-0.083	0.000	-0.055	0.000	-0.055	0.000
$\ln y_1 \ln w_1$	0.020	0.004	0.042	0.000	0.035	0.000	0.035	0.000
$\ln y_1 \ln w_1$	0.015	0.000	0.023	0.000	-0.003	0.030	-0.003	0.000
$\ln y_1 \ln w_1$	-0.018	0.000	-0.023	0.000	-0.007	0.009	-0.007	0.000
$\ln y_1 \ln z$	0.002	0.410	0.026	0.000	0.041	0.000	0.041	0.000
$\ln y_2 \ln z$	-0.022	0.002	0.005	0.445	0.010	0.084	0.010	0.000
$\ln y_3 l \ln z$	0.021	0.000	0.041	0.000	0.072	0.000	0.072	0.000
$\ln w_1 \ln z$	0.063	0.000	0.045	0.000	0.062	0.000	0.062	0.000
$\ln w_2 \ln z$	0.020	0.025	0.004	0.622	-0.033	0.000	-0.033	0.000
T	0.029	0.000	0.038	0.000	0.028	0.000	0.028	0.000
T^2	0.000	0.001	0.000	0.009	-0.001	0.000	-0.001	0.000
$\ln y_1 T$	-0.001	0.014	-0.001	0.000	-0.001	0.000	-0.001	0.000
$\ln y_2 T$	0.004	0.000	0.001	0.174	-0.001	0.350	-0.001	0.003
$\ln y_3 T$	-0.003	0.000	-0.004	0.000	-0.007	0.000	-0.007	0.000
$\ln w_1 T$	0.000	0.698	-0.002	0.002	-0.006	0.000	-0.006	0.000
$\ln w_2 T$	0.005	0.000	0.005	0.000	0.009	0.000	0.009	0.000
$\ln zT$	-0.003	0.022	0.002	0.123	0.008	0.000	0.008	0.000
$\ln NPI$	0.016	0.000	0.015	0.000	0.011	0.000	0.011	0.000

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	Half-normal		Truncated		Kernel		Error	
Location parameter	μ	p-value	μ	p-value	μ	p-value	μ	p-value
μ	n.a.	n.a.	32.220	0.809	20.266	0.627	-0.578	0.000
Heterogeneity					d	p-value	d	p-value
Public savings					-0.058	0.000	0.403	0.000
Free Savings					-0.135	0.000	0.544	0.000
Commercial coop					0.008	0.001	0.141	0.000
Sparda Banken					-0.122	0.000	0.883	0.035
PSD banks					-0.362	0.000	2.003	0.000
Civil servant banks					0.237	0.000	-0.335	0.000
Rural cooperative					0.004	0.036	0.165	0.000
Baden Wuerttemb.					-0.272	0.000	2.697	0.000
Bavaria					-0.244	0.000	1.011	0.000
Berlin					-0.202	0.000	0.404	0.000
Bremen					-0.180	0.000	0.468	0.000
Hamburg					-0.198	0.000	0.551	0.000
Hessia					-0.239	0.000	0.835	0.000
Lower Saxony					-0.178	0.000	0.395	0.000
North Rhine Westp.					-0.218	0.000	0.795	0.000
Rhineland Palatinate					-0.201	0.000	0.569	0.000
Saarland					-0.203	0.000	0.701	0.000
Schleswig Holstein					-0.173	0.000	0.247	0.000
Mecklenburg WP					0.032	0.000	-0.098	0.000
Brandenburg					0.048	0.000	-0.142	0.000
Saxony					0.058	0.000	-0.128	0.000
Thuringia					0.000	0.926	-0.012	0.549
Size class 2					0.038	0.000	0.080	0.000
Size class 3					0.055	0.000	0.056	0.000
Size class 4					0.066	0.000	0.003	0.867

$\sigma = (\sigma_v^2 + \sigma_u^2)^{1/2}; \lambda = \sigma_u/\sigma_v$; BFGS maximisation algorithm; maximum iterations set to 5,000. Step size during iterations for [1] function, [2] gradient and [3] intercept.

Table 9: Parameter estimates alternative profit frontier

PROFIT	Half-normal		Truncated		Kernel		Error	
LL	-17,332		-15,459		-14,064		-14,750	
$\boldsymbol{\sigma}$	0.684	0.000	7.082	0.117	6.875	0.083	4.240	0.000
$\boldsymbol{\lambda}$	2.930	0.000	28.970	0.115	30.808	0.081	17.335	0.000
Iterations	49		76		100		163	
TLF 1)	0.000001		0.0001		0.001		0.001	
TLG 2)	0.000001		0.000001		0.000001		0.000001	
TLB 3)	0.000001		0.000001		0.000001		0.000001	
Variable	b	p-value	b	p-value	b	p-value	b	p‐value
Constant	-8.845	0.000	-9.019	0.000	-8.986	0.000	-9.035	0.000
$\ln y_1$	-0.080	0.095	-0.080	0.093	-0.208	0.000	-0.115	0.011
$\ln y_2$	0.041	0.752	0.103	0.419	-0.015	0.898	0.177	0.162
$\ln y_3$	-0.138	0.004	-0.186	0.000	0.223	0.000	-0.035	0.494
$\ln w_1$	-0.126	0.046	-0.029	0.657	0.085	0.163	-0.046	0.477
$\ln w_2$	0.447	0.000	0.447	0.000	0.423	0.000	0.452	0.000
$\ln z$	1.824	0.000	1.794	0.000	1.649	0.000	1.600	0.000
$\frac{1}{2}\ln y_1 \ln y_1$	0.414	0.000	0.431	0.000	0.429	0.000	0.429	0.000
$\frac{1}{2}\ln y_1 \ln y_2$	0.017	0.000	0.017	0.000	0.006	0.020	0.018	0.000
$\frac{1}{2}\ln y_1 \ln y_3$	0.076	0.000	0.058	0.000	0.087	0.000	0.040	0.004
$\frac{1}{2}\ln y_2 \ln y_2$	0.050	0.000	0.046	0.000	0.008	0.230	0.051	0.000
$\frac{1}{2}\ln y_2 \ln y_3$	0.228	0.000	0.251	0.000	0.303	0.000	0.265	0.000
$\frac{1}{2}\ln y_3 \ln y_3$	-0.080	0.000	-0.077	0.000	-0.106	0.000	-0.100	0.000
$\frac{1}{2}\ln w_1 \ln w_1$	0.091	0.000	0.101	0.000	0.067	0.000	0.098	0.000
$\frac{1}{2}\ln w_1 \ln w_2$	-0.031	0.000	-0.026	0.000	-0.019	0.001	-0.017	0.009
$\frac{1}{2}\ln w_2 \ln w_2$	0.038	0.064	-0.003	0.880	0.001	0.969	-0.013	0.561
$\frac{1}{2}\ln z^2$	0.094	0.000	0.157	0.000	0.155	0.000	0.148	0.000
$\ln y_1 \ln w_1$	0.029	0.000	0.031	0.000	0.003	0.459	0.033	0.000
$\ln y_1 \ln w_1$	-0.025	0.017	-0.026	0.017	-0.018	0.076	-0.026	0.012
$\ln y_1 \ln w_1$	-0.020	0.036	-0.018	0.067	0.007	0.470	-0.027	0.008
$\ln y_1 \ln w_1$	0.123	0.000	0.114	0.000	0.122	0.000	0.137	0.000
$\ln y_1 \ln w_1$	0.007	0.105	0.014	0.002	-0.029	0.000	0.021	0.000
$\ln y_1 \ln w_1$	-0.046	0.000	-0.059	0.000	-0.022	0.017	-0.064	0.000
$\ln y_1 \ln z$	-0.082	0.000	-0.069	0.000	-0.047	0.000	-0.061	0.000
$\ln y_2 \ln z$	-0.273	0.000	-0.294	0.000	-0.343	0.000	-0.293	0.000
$\ln y_3 l \ln z$	-0.056	0.000	-0.062	0.000	-0.019	0.042	-0.058	0.000
$\ln w_1 \ln z$	-0.001	0.962	-0.017	0.159	0.021	0.073	-0.017	0.172
$\ln w_2 \ln z$	-0.095	0.001	-0.072	0.016	-0.126	0.000	-0.092	0.002
T	-0.103	0.000	-0.102	0.000	-0.084	0.000	-0.099	0.000
T^2	-0.002	0.000	-0.002	0.000	-0.002	0.000	-0.001	0.000
$\ln y_1 T$	0.002	0.065	0.003	0.026	0.004	0.005	0.004	0.001
$\ln y_2 T$	0.015	0.000	0.017	0.000	0.010	0.001	0.011	0.001
$\ln y_3 T$	0.016	0.000	0.016	0.000	0.010	0.000	0.017	0.000
$\ln w_1 T$	0.004	0.016	0.005	0.004	0.000	0.787	0.007	0.000
$\ln w_2 T$	0.014	0.000	0.008	0.008	0.010	0.000	0.007	0.020
$\ln zT$	-0.034	0.000	-0.037	0.000	-0.024	0.000	-0.033	0.000
$\ln NPI$	-1.042	0.000	-1.030	0.000	-1.027	0.000	-1.028	0.000

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	Half-normal		Truncated		Kernel		Error	
Location parameter	μ	p-value	μ	p-value	μ	p-value	μ	p-value
μ	n.a.	n.a.	-138.12	0.439	-131.23	0.392	-25.49	0.000
Heterogeneity					d	p-value	d	p-value
Public savings					0.046	0.000	-15.788	0.000
Free Savings					-0.140	0.006	-4.230	0.655
Commercial coop					-0.051	0.000	3.763	0.006
Sparda Banken					-0.091	0.010	8.473	0.227
PSD banks					-0.378	0.000	32.395	0.000
Civil servant banks					-0.126	0.012	24.247	0.004
Rural cooperative					-0.045	0.000	4.129	0.001
Baden Wuerttemb.					-0.325	0.000	-23.687	0.000
Bavaria					-0.382	0.000	-10.770	0.000
Berlin					-0.346	0.000	-10.408	0.064
Bremen					-0.286	0.000	-28.197	0.016
Hamburg					-0.352	0.000	-15.229	0.011
Hessia					-0.250	0.000	-33.945	0.000
Lower Saxony					-0.257	0.000	-30.579	0.000
North Rhine Westp.					-0.241	0.000	-32.321	0.000
Rhineland Palatinate					-0.255	0.000	-31.345	0.000
Saarland					-0.325	0.000	-19.064	0.000
Schleswig Holstein					-0.190	0.000	-28.381	0.000
Mecklenburg WP					0.012	0.504	-9.251	0.001
Brandenburg					0.106	0.000	-10.378	0.001
Saxony					0.111	0.000	-8.295	0.001
Thuringia					0.063	0.000	-12.649	0.000
Size class 2					-0.013	0.109	-5.407	0.000
Size class 3					-0.046	0.000	-7.173	0.000
Size class 4					-0.039	0.021	-8.032	0.035

$\sigma = (\sigma_v^2 + \sigma_u^2)^{1/2}; \lambda = \sigma_u/\sigma_v$; BFGS maximisation algorithm; maximum iterations set to 5,000. Step size during iterations for [1] function, [2] gradient and [3] intercept.

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