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The cost efficiency of German banks: a comparison of SFA and DEA

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Abstract

We investigate the consistency of efficiency scores derived with two competing frontier methods in the financial economics literature: Stochastic Frontier and Data Envelopment Analysis. We sample 34,192 observations for all German universal banks and analyze whether efficiency measures yield consistent results according to five criteria between 1993 and 2004: levels, rankings, identification of extreme performers, stability over time and correlation to standard accounting-based measures of performance. We find that non-parametric methods are particularly sensitive to measurement error and outliers. Furthermore, our results show that accounting for systematic differences among commercial, cooperative and savings banks is important to avoid misinterpretation about the status of efficiency of the total banking sector. Finally, despite ongoing fundamental changes in Europe's largest banking system, efficiency rank stability is very high in the short run. However, we also find that annually estimated efficiency scores are markedly less stable over a period of twelve years, in particular for parametric methods. Thus, the implicit assumption of serial independence of bank production in most methods has an important influence on obtained efficiency rankings.

Keywords: Cost Efficiency, Banks, Stochastic Frontier Approach, Data Envelopment Analysis

JEL: D24, G21, L25

Non-technical summary

To measure the cost efficiency of banks, one should compare observed cost- and output-factor combinations with optimal combinations determined by the available technology (efficient frontier). The method to implement this analysis could be either stochastic or deterministic. The former allows random noise due to measurement errors. The latter, on the contrary, attributes the distance between an inefficient observed bank and the efficient frontier entirely to inefficiency. A further distinction is made between parametric or non-parametric approaches. A parametric approach uses econometric techniques and imposes a priori the functional form for the frontier and the distribution of efficiency. A non-parametric approach, on the contrary, relies on linear programming to obtain a benchmark of optimal cost- and production-factor combinations.

The most popular methods are Stochastic Frontier Analysis (SFA), which is stochastic and parametric, and Data Envelopment Analysis (DEA), which is deterministic and non-parametric. This study analyses on the basis of five criteria to what extent SFA and DEA yield consistent cost efficiency (CE) measures when applied to the same dataset. In particular, we check to what extent they provide different efficiency scores when stratifying the sample according to year, banking group or both dimensions simultaneously.

Our results show very low consistency between SFA and DEA measures, especially when applied to the entire panel sample. First, mean CE according to SFA is substantially higher compared to DEA. This difference becomes smaller when stratifying the sample according to year, banking group or both dimensions simultaneously, since DEA scores improve considerably. Hence, non-parametric methods are much more sensitive to sample heterogeneity. An outlier analysis confirms this result: already after the elimination of only 24 observations mean DEA efficiency increases from 13% to 37%. In turn, SFA results are hardly affected by this exclusion. Second, the identification of efficient or inefficient banks is congruent to a very limited extent only. Rank-order correlation is positive but low. This result is confirmed by little correlation of rankings in the highest and the lowest efficiency quantile across methods, respectively. Third, the stability of efficiency rankings over time is according to both methods quite high, especially in the short run. Even after a time span of up to twelve years, rank order correlations are still fairly high, especially for non-parametric measurement. Consequently, only few banks seem to drastically change their position relative to the majority of competitors. Efficiency rankings are the least stable when measuring efficiency separately per year, especially for parametric methods. Thus, the implicit assumption when using cross-sectional estimators that a bank's production is independent over time is problematic. Finally, our results confirm earlier evidence that efficiency measures are only weakly correlated with more traditional performance indicators, like cost-income and, especially, return ratios. Apparently, efficiency measures contain additional information and should therefore be considered, too, when assessing the success of a bank.

Nichttechnische Zusammenfassung

Bei einer Kosteneffizienzanalyse von Banken werden die beobachteten Kombinationen von Inputpreisen und Outputmengen mit den durch die Technologie beschriebenen Transformationsmöglichkeiten verglichen. Man unterscheidet dabei stochastische und deterministische Methoden. Bei stochastischen Methoden hängen die Abweichungen von der Effizienzgrenze sowohl von der Ineffizienz der Bank als auch von Zufallseinflüssen ab. Bei deterministischen Methoden hängen die Abweichungen ausschließlich von der Ineffizienz ab. Eine weitere Unterscheidung ist jene zwischen parametrischen und nichtparametrischen Methoden. Bei parametrischen Methoden werden a priori Annahmen zur funktionalen Form und zur Verteilung der Effizienz festgelegt. Nichtparametrische Methoden legen hingegen keine funktionale Form fest und nutzen lineare Programmierung, um die Abweichungen zu optimalen Kosten- und Faktorkombinationen zu ermitteln.

Die beiden am häufigsten verwendeten Methoden sind der deterministische und nichtparametrische Ansatz Data Envelopment Analysis (DEA) sowie der stochastische und parametrische Ansatz Stochastic Frontier Analysis (SFA). Die vorliegende Studie untersucht anhand von fünf Kriterien, ob beide Ansätze zu konsistenten Kosteneffizienzmaßen führen. Es wird insbesondere überprüft, inwieweit sich die Effizienzmaße unterscheiden, wenn das gesamte Panel nach Jahren, Bankengruppen oder beiden Kriterien gleichzeitig geschichtet wird.

Die Ergebnisse zeigen niedrige Konsistenz zwischen den zwei Methoden, insbesondere wenn das Gesamtpanel ungeschichtet betrachtet wird. Erstens sind die Effizienzmaße im Mittel deutlich höher bei SFA als bei DEA. Dieser Unterschied wird kleiner, wenn die zu Grunde liegende Stichprobe nach Jahren, Bankengruppen oder beiden Kriterien gleichzeitig geschichtet wird. Dann steigen die DEA-Effizienzzahlen deutlich. Die DEA reagiert sensitiver auf zunehmend heterogene Stichproben, was auch durch die Ergebnisse nach der Bereinigung von extremen Kosten- und Faktorkombinationen bestätigt wird. Bereits der Ausschluß von lediglich 24 Ausreißern bewirkt einen Anstieg der DEA-Effizienz von 13% auf 37%, während die SFA-Maße kaum beeinflußt werden. Zweitens identifizieren beide Ansätze nur bedingt dieselben Institute als besonders effizient oder ineffizient. Die Rangfolgen aus beiden Ansätzen sind schwach korreliert und nur bei einer Schichtung nach Bankengruppe und Jahr einigermaßen stark ausgeprägt. Auch die Untersuchung der niedrigsten und höchsten Effizienzquantile bestätigt die eher geringe Übereinstimmung zwischen den Methoden. Drittens führen beide Ansätze für einen Zeitraum von etwa fünf Jahren zu stabilen Rangfolgen über die Zeit. Selbst über einen Zeitraum von 12 Jahren sind die Korrelationen von Rangfolgen noch relativ groß, insbesondere bei der DEA. Nur wenige Institute entwickeln sich also über die Zeit stark unterschiedlich relativ zur Mehrheit der Banken. Mittel- und langfristige Rangfolgen sind dann am instabilsten, wenn die Schätzung je Jahr erfolgt. Die implizite Annahme zeitlicher Unabhängigkeit von Produktionsplänen bei der Ermittlung von Bankkostenfunktionen mit Querschnittsschätzern scheint somit problematisch. Schließlich bestätigen unsere Ergebnisse frühere Evidenz, dass Effizienzmaße und traditionelle Indexzahlen, wie Kosten- und vor allem Ertragskennziffern, unterschiedliche Informationen enthalten. Geringe Korrelationskoeffizienten zwischen DEA- und SFA-Maßen mit traditionellen Indikatoren sind ein Indiz dafür, dass Effizienzmaße hinzugezogen werden sollten, wenn die Leistungsfähigkeit einer Bank beurteilt wird.

Contents

The Cost Efficiency of German Banks: A Comparison of SFA and DEA[1]

1 Introduction

Financial institutions around the world experienced substantial changes in the last 15 years (OECD, 2000). Technological progress, reduced information costs, fiercer competition among both bank and non-bank financial intermediaries and ongoing deregulation in the wake of the creation of a Single European Market for financial services all led to substantial changes in numerous financial systems.

As pointed out by the European Central Bank (2005), the largest European banking market, Germany, exhibits some of the most marked changes in terms of both market structure and performance. In a consolidating market environment, banks continue their efforts to cope with new competitive challenges by improving the efficiency of their operations.

To assess banks' ability to increase efficiency, both regulators and practitioners rely increasingly on economic theory to measure the efficiency of banks and compare institutes with each other. Given the importance of efficiency measures as a tool for policy makers and markets participants the early remark of Bauer et al. (1998) is disturbing: efficiency scores vary considerably across studies.

Only few banking studies in general and even less of those examining the German banking system, investigate the reasons for these differences more profoundly.[2] In this paper, we therefore follow the suggestion of Bauer et al. (1998) and expose an identical data set of commercial, savings and cooperative banks to the two major alternative methodologies encountered in the literature: Stochastic Frontier Analysis (SFA) on the one hand and Data Envelopment Analysis (DEA) on the other.

While it is not necessary to achieve consensus on the best frontier approach for efficiency analysis, it is of crucial importance to be aware of potentially conflicting information the two methods may provide. By using multiple techniques, especially parametric versus non-parametric techniques, the robustness of results can be put into perspective. Charnes et al. (1978) refer to this approach as methodological cross-checking and we check the consistency of efficiency measures according to five criteria of Bauer et al. (1998): efficiency levels, efficiency rankings, the identification of extreme performers, time consistency and consistent correlations with traditionally employed accounting indicators.

The paper is organized as follows. Section 2 reviews the related Literature. Section 3 introduces the empirical and linear programming methods used here. Section 4 describes the data. We discuss our findings in section 5 and conclude in section 6.

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[2]An exception is Bos et al. (2005), who discuss the stability of efficiency according to SFA.

2 Related Literature

Bank efficiency studies are fairly abundant by now. But only a few apply two or more techniques to an identical data set, especially European data (Weill, 2004). Studies that compare parametric and non-parametric techniques are Ferrier and Lovell (1990), Sheldon (1994), Resti (1997), Bauer et al. (1998), Casu and Girardone (2002), Weill (2004) and Beccalli et al. (2006)[3]. We briefly examine some of the evidence provided by these comparisons here. We report, in particular, the results which concern our five consistency checks.

An early study that compares alternative frontier techniques is Ferrier and Lovell (1990). They analyze the cost structure of 575 US banks for the year 1984 using both the SFA and DEA methodologies. They find higher efficiency scores with DEA compared to SFA, namely 80% and 74%, respectively. They conclude that DEA is sufficiently flexible to envelop the data more closely than the translog cost frontier. However, efficiency scores are not significantly correlated thus indicating that other factors not controlled for may drive the obtained wedge between the two measures. European evidence is provided by Sheldon (1994). He analyzes the cost efficiency of Swiss banks with SFA and DEA in the period from 1987 to 1991. While results from DEA indicate that the average degree of cost efficiency is about 56%, SFA yields only 3.9% mean efficiency. This substantial deviation from usually obtained magnitudes of around 80% obtained for US and European studies casts some doubt as to an appropriate specification of the cost function (Amel et al., 2004). Likewise, he reports insignificant rank-order correlation of 1%, indicating that no relationship exists between the two groups of efficiency scores. These results that two alternative methods to implement an identical theoretical cost minimization problem should not be correlated are remarkable.

And, in fact, Resti (1997) provides very different results. He analyzes the cost efficiency of 270 Italian banks over the period 1988-1992. He compares the parametric and non parametric efficiency scores and finds that econometric and linear programming results do not differ substantially. Moreover, contrary to Ferrier and Lovell (1990) and Sheldon (1994), he reports higher efficiency scores between 81% and 92% for SFA as opposed to DEA scores between 60% and 78%. Rank correlation between SFA and DEA is statistically significant at the 1% level and ranges from 44% to 58%. The rank ordering of firm specific inefficiency is strongly correlated over time, although it is more persistent with DEA than with SFA.

The Bauer et al. (1998) study is among all the most significant, given the application of four approaches SFA, DEA, Thick Frontier Analysis (TFA) and Distribution Free Analysis (DFA) on a data set of 683 US banks over the period 1977-1988.[4] They suggest six consistency conditions to analyze the robustness of frontier efficiency measures. They compare the efficiency distributions, the rank order correlation of the efficiency distributions, the correspondence of best-practice and worst-practice

[3]Studies, that compare parametric techniques include Bauer et al. (1993), Allen and Rai (1996), Hasan and Hunter (1996), Berger and Mester (1997) and Berger and Hannan (1998). Their results differ with regard to the efficiency scores and the rank correlations between techniques.

[4]TFA (Berger and Humphrey, 1991) employs only the best performers defined as those in the lowest average cost quartile for their size class. DFA (Berger, 1993) assumes only a constant core inefficiency that persists over time but imposes no further distributional assumptions on efficiency.

banks across techniques, the stability of measured efficiency over time, the consistency of efficiency with market competitive conditions and the consistency with standard non-frontier performance measures. For each approach they calculate a measure of single year efficiency and a measure of total years efficiency based on one set of banks over the entire time period. Mean efficiency of parametric techniques averages 83% while mean efficiency for the nonparametric approaches is only around 30%. Nonparametric and parametric techniques give only very weak consistency ranking with each other: rank-order correlation is 10%. All the methods are stable over time although DEA generally shows slightly better stability than the parametric methods. On the other hand, the parametric efficiency scores are generally consistent with the standard performance measures, while DEA efficiency scores are much less so. In sum, Bauer et al. (1998) conclude that there is no single correct approach to specify an efficient frontier. Instead, both measures seem to react to varying degrees to particularities of the data. Thus, reporting methodological cross-checks are important to ensure that policy makers are aware of the different information contained in efficiency measures derived with alternative methods.

In a more recent study, Casu and Girardone (2002) evaluates the cost characteristics, profit efficiency and productivity change of Italian financial conglomerates during the 1990s using SFA, DFA and DEA. Efficiency measures from stochastic and deterministic frontiers are reasonably similar in magnitude and also show similar variation in efficiency levels.[5] Despite these similarities in range and variance of the efficiency score, the trend in the DEA cost efficiency is increasing between 1996 and 1998 and shows a rather sharp decrease in 1999. In turn, SFA estimates exhibit a steady improvement in cost efficiency. Not surprisingly, DFA efficiency estimates are consistent with the DEA scores rather than with the SFA and display a decreasing trend of efficiency. Weill (2004) also checks the robustness of SFA, DFA and DEA. He measures the cost efficiency of 688 banks from five European countries (France, Italy, Germany, Spain, and Switzerland) over the period from 1992 to 1998. He compares mean efficiencies, correlation coefficients between methodologies and the correlation with standard measures of performance. Efficiency scores do not differ substantially across techniques and are positively correlated between SFA and DFA. At the same time, there is no positive relationship between any parametric approach and DEA. All approaches provide efficiency scores that are correlated with standard measures of performance. Beccalli et al. (2006) measure cost efficiency of stock-market listed European banks in 1999 and 2000. They investigate the link between efficiency measures and the market performance of financial institutions by means of SFA and DEA and find that percentage changes in stock prices reflect percentage changes in cost efficiency, particularly those derived from DEA. Furthermore, SFA efficiency scores are slightly higher than DEA scores, namely 85% versus 83%[6] and DEA efficiency scores are more dispersed compared to SFA.

In sum, more recent studies find that SFA efficiency scores are generally higher compared to DEA scores. This may reflect the different treatment of stochastic noise and the ability to control for heterogeneity. At the same time, studies that investigate the differences across methods more systematically show that efficiency measures differ not only in terms of mean industry efficiency. Efficiency rankings, their stability over time and the consistency with traditionally employed performance

[5]Standard deviations are around 10%.

[6]Input- versus output-oriented DEA model yield virtually identical results.

measures contain important additional information for policy making purposes. Finally, it is noteworthy that with the exception of Bauer et al. (1998), none of these cross-checking exercises quantifies differences for a banking system as a whole but focus on distinct time intervals and/ or particular groups of banks in the system, such as large, stock-listed institutes. In fact, smaller samples that compare only a fraction of the market may even underestimate the differences of DEA and SFA measures since they are likely to sample already more akin banks. Let us therefore turn next to our comparison of DEA and SFA for the German banking industry as a whole.

3 Efficiency: Concepts and Measurement

3.1 Concepts

Farrell (1957) laid the foundation to measure efficiency and productivity studies at the micro level. His contribution highlighted new insights on two issues: how to define efficiency and productivity, and how to calculate the benchmark technology and efficiency measures. The fundamental assumption is to depart from the assumption of perfect input-output allocation but to allow for inefficient operations. Inefficiency is defined as the distance of a firm from a frontier production function accepted as the benchmark.[7] The basis for this measure is the radial contraction/expansion connecting inefficient observed points with (unobserved) reference points on the production frontier. If a firm's actual production point lies on the frontier it is perfectly efficient. If it lies below the frontier then it is inefficient, with the ratio of the actual to potential production defining the level of efficiency of the individual firm (Decision Making Unit, DMU). Farell proposed efficiency consists of two components: technical efficiency and allocative efficiency. The former reflects the ability of a DMU to minimize input use as to produce a given amount of output. The latter reflects the ability of a DMU to use inputs in optimal proportions, given their respective prices and the production technology. Together, these two measures represent a total efficiency measure (Coelli et al., 1997). Efficiency ratios take on a value between zero and one, where one indicates that the DMU is fully efficient. For example, an efficiency score measured against a cost frontier of 90% signifies that the DMU could have reduced costs by 10% without altering it's output vector.

The estimation of efficiency can be categorized according to the assumptions and techniques used to construct the efficient frontier. On the one hand, parametric methods *estimate* the frontier with statistical methods. On the other hand, nonparametric methods rely on linear programming to *calculate* piecewise linear segments of the efficient frontier. Parametric methods impose an explicit functional form for both the frontier and deviations from it, that is inefficiency. Nonparametric methods, in contrast, do neither impose any assumptions about functional form of the frontier nor any distributional assumptions about inefficiency. This entirely deterministic construction of the frontier attributes the entire difference between an inefficient observed DMU and an efficient reference DMU on the frontier exclusively

[7]This concept was opposed to a notion of average performance underlying most of the econometric literature on the production function up to the time of Farrell‘s paper.

to inefficiency. Estimation of the frontier, in turn, allow for random noise in the analysis. This involves the estimation of a stochastic frontier. Thus, in the context of a production function, the output of a firm is a function of inputs subject to a production technology and inefficiency arising in the employment of that technology. Non-parametric methods, in turn, also allows random error in observed input-output combinations.

3.2 Data Envelopment Analysis

Consider first Data Envelopment Analysis (DEA). It was introduced by Charnes et al. (1978), CCR henceforth for short. They developed the piece-wise-linear convex hull approach to frontier estimation proposed by Farrell (1957) in a model which has an input orientation and assumes constant return to scale, in the following CCR model. Subsequent papers have considered alternative sets of assumptions, such as variable return to scale (VRS) and output orientation (Banker et al., 1984). The originally suggested input oriented CCR is formulated as:

$$\begin{aligned} & \min_{\lambda} \theta \\ st \quad & -y_o + Y\lambda \geq 0, \\ & \theta x_o - X\lambda \geq 0, \\ & \lambda \geq 0, \end{aligned} \tag{1}$$

where θ is a scalar, λ is a N*1 vector of constants, y_o is an output vector for a DMUo, Y is the matrix of outputs of the other DMUs and the number of DMUs ranges in $j = 1...n$, x_o is the vector of input of DMUo and X is the matrix of input of the other DMUs. The value of θ obtained will be the efficiency score for the o-th DMU where $0 \leq \theta \leq 1$. In case θ has value equal to 1 the DMU lies on the frontier and is fully efficient. Essentially, the optimization procedure takes the o-th DMU and then seeks to radially contract the input vector, x_o, as much as possible while still remaining within the feasible input set. The radial contraction of the vector x_o produces a projection point $(X\lambda, Y\lambda)$ on the efficient frontier and the constraints ensure that this projection belongs to the feasible set (Coelli et al., 1997). DEA generates the efficiency frontier as a linear combination of the efficient observed data instead of assuming an explicit functional form a priori. The difference between the vector x_o and the projection point $(X\lambda, Y\lambda)$ measures inefficiency.

The original CCR model assumes constant return to scale (CRS), an inappropriate assumption for most banking studies in general and particularly inappropriate for Germany's heterogenous three-pillar banking system (Hackethal, 2004). It is therefore reasonable to adopt variable return to scale (VRS), which ensures that a firm is compared only with firms of a similar size. This implies to add a constraint $N1\lambda = 1$ to the CCR problem, where $N1$ is a N*1 vector of ones. The model with VRS creates the frontier as a convex hull of intersecting planes in contrast to the model with CRS, which forms a conical hull. The VRS model thus envelops the data more tightly and provides efficiency scores that are equal or greater than those of the CRS model (Banker et al., 1984).

The CCR model focuses on the technical-physical aspects of production. It is appropriate if behavioral assumptions of firms' objectives like cost minimization or profit maximization cannot be made. Alternatively, the model may prove useful if unit price and unit cost information are either unavailable or of questionable quality due, for example, to substantial measurement error. If economic objective functions are reasonable and if reliable price information is available, however, DEA can also be used to identify allocative efficiency (Cooper et al., 2000). Since we assume indeed that banks minimize cost in Germany, we consider in this paper input oriented efficiency with variable return to scale.[8] We write the according cost model as:

$$\min \sum_{i=1}^{m} c_{io} x_{io}$$

$$\begin{aligned} st \qquad & x_{io} \geq \sum_{j=1}^{n} x_{ij}\lambda_j, (i = 1, ..., m) \\ & y_{ro} \leq \sum_{j=1}^{n} y_{rj}\lambda_j, (r = 1, ..., s) \\ & \sum_{j=1}^{n} \lambda_j = 1, \\ & \lambda_j \geq 0 \forall j, \end{aligned} \tag{2}$$

where $j = 1, ..., n$ are the number of bank, $i = 1, ..., m$ are input volumes used by bank j, $r = 1, ..., s$ measures the volume of output r and c_{io} is the unit cost of the input i of bank DMU_o which is the benchmark projection that can be different from one bank to another. The minimization problem is calculated for each bank of the sample, thus identifying for each a benchmark combination of inputs and cost. Every DEA model assumes a returns-to-scale characteristics that is represented by the ranges of the sum of the intensity vector λ, i.e., $L \leq \lambda_1 + \lambda_2 + ... + \lambda_n \leq U$. Here we compute variable returns to scale and use $L = U = 1$, i.e. we consider convex hull representation. Our model allows substitutions in inputs. Based on an optimal solution (x^*, λ^*) of the above problem, the cost efficiency of DMU_o is defined as

$$CE_o = \frac{c_o x^*}{c_o x_o}, \tag{3}$$

where CE_o is the ratio of minimum cost to observed cost for the oth firm. Clearly, this approach implies that all observed input-cost combinations are measured with no error. Outliers may be classified as very efficient simply because data error

[8] In fact, one may argue that both banking groups do not follow strict profit maximization. For example, savings banks mention as an objective to promote saving and capital accumulation and the funding of public tasks. Likewise, cooperatives aim to promote the acquisition and business activities of the members. While banks may be consciously willing to forego profit margins, we argue here that cost minimization is a necessary condition for any bank since no competitor can offer similar products at higher cost in the long run.

implies no comparison unit for these institutes or they may simply be unique. Since this hypothetical bank co-determines the frontier relative to which all other peers are evaluated, mean efficiency may be low as the majority of banks are located far above this benchmark. If we assume that measurement errors occur randomly, a stochastic approach can alleviate the problem.

3.3 Stochastic Frontier Analysis

Aigner et al. (1977), Battese and Corra (1977), Meeusen and Van den Broek (1977) independently proposed to estimate a stochastic production frontier. The model is denoted in logs as $ln(y_j) = lnx_j\beta + v_j - u_j$, where x_j denotes an input vector for firm j, v_j depicts random error added to the non-negative inefficiency term, u_j. Random error, v_j, accounts for measurement error and other random factors affecting the value of the output variable, together with the combined effects of unspecified input variables in the production function. The model is stochastic because the upper limit is determined by the stochastic variable $exp(x_j\beta + v_j)$. The random error,v_j, can be positive or negative and so the stochastic frontier outputs vary relative to the deterministic part of the frontier model, $exp(x_j\beta)$ (Coelli et al., 1997).

To estimate the stochastic frontier model, we need to assume a functional form. Since banking is a multi-output industry, specification of a production function is not feasible. Moreover, behavioral assumptions such as cost minimization are appropriate for banks and thus we follow the consensus in the literature and use duality to specify a cost frontier.[9] The stochastic cost frontier has the following general log form $lnC_j = f(lny_{r,j}, lnc_{i,j}) + \varepsilon_j$. Here, C_j is total cost for firm j, $y_{r,j}$ measures the r-th output of firm j, and $c_{i,j}$ is the price of the i-th input of firm j. The error term, ε_j is composed of the two components v_j and u_j as $v_j + u_j$. The random error term v_j is assumed iid with $v_j \sim N(0, \sigma_v^2)$ and independent of the explanatory variables. The inefficiency term is iid with $u_j \sim N|(0, \sigma_u^2)|$ and independent of the v_j. It is drawn from a non-negative distribution truncated at zero.[10] We specify a multi-product translog cost function and estimate:

$$\begin{aligned} lnC_j &= \alpha_0 + \sum_{rj} \beta_r lny_{rj} + \sum_{ij} \beta_i lnc_{ij} + \frac{1}{2} \sum_i \sum_k \beta_{ik} lny_{ij} lny_{kj} \\ &+ \frac{1}{2} \sum_i \sum_z \beta_{iz} lnc_{ij} lnc_{zj} + \sum_r \sum_i \beta_i lny_r lnc_i + v_j + u_j \end{aligned} \tag{4}$$

where C is total operating cost, $y_r, r = 1,..,3$ are outputs, $c_i, i = 1,...,3$ are input prices and α_0 is an intercept accounting for all other cost determinants. Since inefficiency leads to higher than optimal costs, note that the inefficiency term u_j is added. We define banking in- and outputs in line with the intermediation approach and describe our data in section 4. The use of duality implies the necessity to impose the following homogeneity restrictions:

[9] See for example Beattie and Taylor (1985) for the use of duality between production maximization and cost minimization problems.

[10] This assumes that the majority of banks is close to full efficiency.

$$\sum_r \beta_r = 1, \sum_{i,z} \beta_{iz} = 0, \sum_i \beta_i = 0. \qquad (5)$$

As in Lang and Welzel (1996), we therefore normalize total costs and input prices by the price of labor. We estimate firm-specific efficiency scores as the conditional expectation of u_j given ε_j (Jondrow et al., 1982). Efficiency measures are calculated as $expE[-u|\varepsilon]$ and take on values between 0 and 1, where the latter indicates a fully efficient bank. The value indicates the percentage of observed costs that would have been sufficient to produce the observed output if the bank was fully efficient.

Clearly, the ability of this approach to account for previously described measurement error through v comes at a cost. Identification of the two different total error components u and v requires, first, the distributional assumptions outlined above and, second a re-parametrization during maximum-likelihood estimation (MLE). We first estimate equation (4) with OLS and use slope parameters as starting values in the MLE. In line with Aigner et al. (1977), we employ a re-parametrization of $\sigma = \sqrt{(\sigma_u^2 + \sigma_v^2)}$ and $\lambda = \sigma_u / \sigma_v$. A useful implication is that λ provides an opportunity to test the validity of imposed assumptions. It indicates the ratio of standard deviation attributable to inefficiency relative to the standard deviation due to random noise. An insignificant estimate of λ means that no inefficiency prevails. Clearly, as $\lambda \rightarrow 0$, σ_u^2 goes to zero or σ_v^2 goes to infinity. Hence, no inefficiency exists or all deviations are due to random noise. Likewise, for $\lambda \rightarrow \infty$ we note that $\sigma_u^2 \rightarrow \infty$ or $\sigma_v^2 \rightarrow 0$, which implies that all deviation are explained by inefficiency. Then, inefficiency is 'deterministic' and resembles approaches excluding random noise, such as DEA.

4 Data and Variables

We obtained data from the Deutsche Bundesbank on balance sheets and profit and loss accounts that were reported between 1993 and 2004.[11] To define input and output items we follow the intermediation approach of Sealey and Lindley (1977): The primary function of banks is to channel financial funds from savers to investors. To provide output y_r, banks demand input quantities x_i at given prices c_i that minimize total operating costs C.

In line with the literature we define three input and output categories. Input quantities are fixed assets x_1, such as branches and administrative buildings; labor x_2, measured as full-time equivalents (FTE); and borrowed funds x_3, measured as the volume of deposits and bonds. Input prices c_i are derived per bank as depreciation relative to fixed assets, personnel expenses relative to FTE and interest expenses relative to total borrowed funds, respectively. As outputs we define the volume of interbank and customer loans, y_1 and y_2, on the one hand and investment in stocks and bonds, y_3, on the other.

[11] All data had been taken in current values as reported in the Deutsche Bundesbank Statistics. A detailed description of individual position can be obtained from the according reporting forms, available at http://www.bundesbank.de/meldewesen.

Table 1: Cost and production variables by banking group between 1993 and 2004

Variables			**Comm'cial**	**Savings**		**Cooperatives**		**Total**
				Central	*Regional*	*Central*	*Regional*	
Interbank loans	y_1	Mean	2,100	34,900	132	27,000	31	382
		SD	11,100	30,400	257	22,100	98	4,440
Commercial loans	y_2	Mean	4,380	35,300	891	11,100	144	757
		SD	23,400	27,300	1,400	11,300	366	6,920
Securities	y_3	Mean	2,020	20,200	392	16,400	52	365
		SD	12,500	19,200	526	19,000	147	3,900
Fixed assets	x_1	Mean	36	151	23	108	4	11
		SD	159	169	30	129	8	48
Employees	x_2	Mean	965	2,875	397	2,074	68	211
		SD	4,283	2,352	460	1,795	107	1,195
Borrowed funds	x_3	Mean	8,370	88,500	1,390	54,600	223	1,480
		SD	46,500	72,700	2,010	51,300	546	14,800
Price of fixed assets	c_1	Mean	122.8	30.3	16.3	23.9	15.7	23.2
		SD	1,761.6	35.1	12.9	9.9	105.8	469.4
Price of labor	c_2	Mean	83.1	74.2	48.2	67.1	49.3	51.5
		SD	429.3	20.5	220.7	14.7	22.8	151.3
Price of funds	c_3	Mean	7.58	5.05	3.77	4.34	3.63	3.94
		SD	97.6	1.1	0.8	1.0	0.8	25.5
Total operating cost	C	Mean	471	4,780	84	2,620	14	84
		SD	2,400	3,790	120	2,350	30	767
Observations	N		2,331	156	6,941	39	24,725	34,192

Notes: All variables measured in millions of €except x_2 (in FTE), c_2 (in thousands of €) and c_3 (percentage points).

As pointed out by Hackethal (2004), German banking is quite heterogeneous. The data in table 1 illustrates this vividly as mean sizes in both the input and output dimensions vary considerably across banking groups. To underline this heterogeneity we standardize the cost and production variables of saving and cooperative banks by the mean of commercial banks. The results are shown in table 2. These statistics underpin not only the differences prevailing between the three pillars but also the differences apparently existing within each sector between regional banks on the one hand and nationally active ones on the other. For example, regional saving banks use only half of the input in comparison to commercial banks, and regional cooperatives use even less. The output quantities seem to follow the same trend: Commercial banks produce almost five times more than saving banks and ten times more than cooperative banks.

These simple summary statistics might cast doubt on whether we could possibly compare such different institutes as, for example, large commercial banks and small regional cooperative banks. Since we are in this study first and foremost interested in the stability of efficiency measures across methodologies, we choose to compare all banks to a common frontier as to obtain a holistic picture of the relative performance in the industry as a whole. Given that all banks ultimately compete with one another, we measure their respective performance here against a common benchmark. In fact, we are exactly interested to learn how well (or not) each method can fit a shared envelope to this banking industry where, after all, consumers applying for a loan consider all banks an option.

Table 2: Standardization of Cost and Production Variables by Commercial Banks

Variables		**Comm.**	**Savings-C.**	**Savings-R.**	**Coop-C.**	**Coop-R.**
Interbank loans	y1	1.00	16.62	0.06	12.86	0.01
Commercial loans	y2	1.00	8.06	0.20	2.53	0.03
Securities	y3	1.00	10.00	0.19	8.12	0.03
Fixed assets	x1	1.00	4.19	0.64	3.00	0.11
Employees	x2	1.00	2.98	0.41	2.15	0.07
Borrowed funds	x3	1.00	10.57	0.17	6.52	0.03
Price of fixed assets	c1	1.00	0.25	0.13	0.19	0.13
Price of labor	c2	1.00	0.89	0.58	0.81	0.59
Price of funds	c3	1.00	0.67	0.50	0.57	0.48
Total operating cost	C	1.00	10.15	0.18	5.56	0.03
Bank year observations	N	2,331	156	6,941	39	24,725

5 Results

In the vein of Bauer et al. (1998), we test the robustness of cost efficiency measures from SFA and DEA with five consistency checks. The efficiency estimates should be consistent regarding levels, rankings, the identification of best and worst banks, the stability over time and the relation to non-frontier measures of performance.

We hypothesize that especially two characteristics affect SFA and DEA results: bank's business focus as exhibited by different banking group membership (Bos et al., 2005) and developments over time that affected Germany's banking pillars differently (Hackethal, 2004). Therefore we expand the suggestion of Bauer et al. (1998) and estimate frontiers not only for annual and pooled samples. Additionally, we stratify our sample according to banking groups. This results in four samples exposed to SFA and DEA, respectively: (i) pooled over 12 years and three pillars; (ii) pooled banking groups per year; (iii) separate banking group frontiers pooled over all years; and (iv) banking-group specific frontiers per year. Clearly, if these two characteristics affect SFA and DEA efficiency scores the most, we expect for the last sample the least differences between both measures.

5.1 Efficiency Distributions

A number of distributional characteristic of the efficiency scores generated by the parametrical and non-parametrical methodologies are reported in table 3.

Across all four different samples, mean efficiency according to SFA is 84% while mean efficiency averaged only 55% for DEA. The most striking result from table 3 is, however, not the absolute difference between DEA and SFA efficiency measures, which may only partly be traced back to the additional degrees of freedom from interaction terms and the intercept in the SFA specification. Instead, either methods reacts markedly different when increasing the homogeneity of the sample. While SFA mean efficiency increases by a mere 7 percentage points, minimizing differences across banking groups and time leads to a substantial increase in DEA scores from as low as 13% to 85% in the most stratified sample. The inconsistency between parametric and nonparametric efficiency measures that do not account for these factors is further illustrated by standard deviations, skew and kurtosis of SFA and

Table 3: Cost efficiency according to SFA and DEA

	SFA				DEA			
	All	*Years*	*Groups*	*Both*[1)]	*All*	*Years*	*Groups*	*Both*
Mean	82.8	81.1	87.3	87.8	13.0	46.5	76.3	85.1
Maximum	99.4	99.8	99.7	99.9	100.0	100.0	100.0	100.0
Minimum	3.0	5.1	3.5	4.7	0.5	1.6	0.6	1.6
Standard deviation	9.0	10.4	9.8	9.5	17.7	20.0	16.9	11.8
Skewness	-2.19	-1.32	-2.90	-2.91	2.39	0.18	-2.37	-2.30
Kurtosis	11.77	6.51	14.90	15.42	9.08	2.95	9.97	11.53
N	34,192	34,192	34,192	33,213	34,192	34,192	34,192	34,192

Notes: [1)] Excluding central cooperative and savings banks due to too low degrees of freedom.

DEA efficiency. Consider, for example, efficiency based on the full sample pooled across years and groups, which marks the standard approach in most studies.

The standard deviation of DEA scores is almost twice as high as that of SFA. This already suggests that failure to control for systematic differences yields fundamentally different scores between the two methods. Perhaps even more importantly, the skew indicates that both methodologies locate the mass of banks on virtually opposite ends of the efficiency distribution. In fact, under DEA almost 80% of banks exhibit efficiency below 30%. In contrast, the SFA identifies around 80% of banks enjoying efficiency in excess of 80%. The latter means that banks are, first, relatively close to one another in terms of efficiency levels and, second, closer to full efficiency than to full inefficiency.

Since true inefficiency remains unobservable it is not possible to validate, which of the two methods is the correct one. However, it is interesting to note that not only first moments are affected by the use of alternative samples. Table 3 shows that while the choice of increasingly homogenous samples does not affect the dispersion of SFA scores to a great extent, the standard deviation of DEA efficiency scores is approximately halved when using the most detailed sample of annual group-specific frontiers. Consequently, DEA may simply suffer from limitations to find appropriate reference units for a diverse group of DMUs and thus projects the mass of banks onto a frontier that is constituted by only few extreme performers. However, some extreme input-cost observations may simply be outliers solely due to measurement error. Since DEA neglects such random error, one obvious explanation for differences between DEA and SFA scores is the sensitivity of the former approach to such outliers.

This is because DEA envelopes the data. Implicitly, one supposes that all observed units belong to the attainable set. In the presence of superefficient outliers, envelop calculations can be different since they are very sensitive to extreme observations. There are many reasons why an observation might be atypical. An observation could be an outlier because it contains an error (bad coding, etc.), or because it presents features which are too different from the remainder of the data set to which it is compared. Detecting outliers is not an easy task for multivariate analysis (Simar, 2003). In addition, most of the standard geometrical methods for detecting outliers in multivariate set-ups do not take the frontier aspect of the problem into account (Wilson, 1993).

Here, we take the frontier problem into account and identify the outliers by inspecting the DMUs which build the convex hull in DEA. In particular we search for atypical efficiency scores by year and by pillars in order to identify the subset of DMUs which may distort the frontier. We find that the the most extreme efficiency scores for the full sample are primarily attributable to commercial banks and to regional cooperative banks in the years 1995, 1996, 1998, 1999, 2000, 2003 and 2004. We drop banks when two criteria are fulfilled. First, they need to belong to the frontier. Second, they simultaneously constitute reference units for more than 1000 other banks. In all, we eliminate 24 observations from the data set and then recalculate the efficiency score with both the DEA and SFA methods. In table 4 we report the according results excluding outliers.

Table 4: Sensitivity of efficiency measures to outliers

	SFA				**DEA**			
	All	*Years*	*Groups*	*Both*[1)]	*All*	*Years*	*Groups*	*Both*
Mean	84.3	83.9	87.4	88.1	36.5	56.1	77.4	85.5
Maximum	98.3	99.7	99.2	99.9	100.0	100.0	100.0	100.0
Minimum	53.2	51.7	25.2	20.3	1.2	1.7	1.2	1.7
Standard deviation	7.5	7.2	9.6	8.8	12.5	15.0	13.7	10.6
Skewness	-1.67	-0.72	-2.85	-2.58	2.16	0.59	-1.68	-1.76
Kurtosis	6.73	4.00	14.22	12.86	9.62	3.20	7.31	8.27
N	34,168	34,168	33,973	33,197	34,168	34,168	34,168	34,168

Notes: [1)] Excluding central cooperative and savings banks due to too low degrees of freedom.

Bearing in mind that we merely excluded 24 observations out of approximately 34,000 from our sample, the reported improvement in DEA efficiency scores from 13.0% to 36.5% is remarkable. Our findings support earlier conclusions in the financial economics literature that nonparametric methods are sensitive to outliers. In turn, comparing results in tables 3 and 4 shows that SFA is much more stable since efficiency estimates are virtually unchanged.[12] Apparently, the presence of outliers is captured in SFA appropriately by the random term as confirmed by the results. Summarizing, the effect of removing even a small number of outliers has a strong influence on DEA efficiency scores and a very limited one for SFA. We conclude therefore that accounting for random noise or for outliers in bank efficiency analyses is important even when using comparably high quality data. Henceforth, we report results that exclude the above identified outliers.

5.2 Efficiency Rankings

Although efficiency levels differ between techniques, it is still possible that these methods generate similar rankings of banks. The identification of which financial institutions are more efficient than others is usually more important for regulatory policy decisions than the absolute measure of efficiency levels. Indeed, Bauer et al. (1998) note that if methods do not rank institutions similarly, then policy conclusions may be fragile and depend on which frontier approach is employed. Table 5 depicts Spearman rank-order correlation coefficients across methodologies and samples.

[12] Since total error is reduced by the exclusion of outliers SFA efficiency scores also improve, however, by only a mere 1.5% in the most sensitive pooled sample.

Table 5: The stability of ranks across methods

	SFA				DEA		
	All	*Years*	*Groups*	*Both*[1)]	*All*	*Years*	*Groups*
SFA *Year*	73.9	100.0					
SFA *Group*	78.8	57.2	100.0				
SFA *Both*	74.0	56.1	92.4	100.0			
DEA *All*	18.8	10.4	22.7	28.5	100.0		
DEA *Years*	13.5	16.9	19.3	25.0	70.7	100.0	
DEA *Groups*	20.3	12.3	44.3	47.6	64.4	59.4	100.0
DEA *Both*	28.0	14.5	43.3	46.7	62.1	52.8	83.5

Notes: All correlation coefficients are significant at the 1% level. [1)] Excluding central cooperative and savings banks due to too low degrees of freedom.

Within each family of benchmarking methods, rankings are fairly consistent. Rank-order correlations measured as Spearman's ρ are positive, high and significant at the 1% level. Note, however, that correlations are on average higher for SFA (74%) compared to DEA (50%). Hence, even after the elimination of potential self-identifiers in nonparametric methods, the gradual move towards more akin peers compared in the analysis still yields different rankings of banks.

More importantly, our results point out that across DEA and SFA rankings differ considerably. The average rank order correlation between SFA and DEA, shown in the lower left panel of table 5, is only around 20% . An interesting result is that the rank correlation improves as long as DEA is used for more homogenous sample: The correlation between both measures obtained from banking-group specific samples, both pooled and annually, and the respective two parametric methods is on average 45%. Thus DEA and SFA can be relied upon to generally rank the banks in the same order only for relative homogeneous samples. This seems to be a drawback of DEA, since the standard non-parametrical methods are not able to account for heterogeneity and interpret difference between banks only as inefficiency. Interestingly, table 5 also allows to infer for the relative importance of group effects versus time effects for the two methods when passing from the fully pooled sample to the stratified subsamples. While for SFA, the time effect is somewhat more pronounced than the group effect (reducing correlation from 100,0% to 74,0% instead of 78,8%), for DEA the group effect is especially severe when compared to the time effect (correlation reduces to 64,4% resp. 70,7%).

5.3 Identification of Extreme Performers

Even if the methods do not always rank the banks similarly, they may still be useful for regulatory purposes if they are consistent in identifying which are the most and least efficient institutions. Table 6 shows the correspondence of identified extreme performers across methodologies.

The lower left triangle of the matrix in table 6 reports for each pair of frontier efficiency techniques the proportion of banks that are identified simultaneously by both techniques to exhibit efficiency scores in the lowest quarter. For example, of the banks identified in the bottom 25% by DEA in the pooled sample, 22.37% are

Table 6: Best and worst performing banks

	SFA				DEA			
	All	*Years*	*Groups*	*Both*	*All*	*Years*	*Groups*	*Both*
SFA *All*		80.62	83.01	78.62	28.34	20.52	24.58	25.68
SFA *Year*	44.41		73.88	71.2	22.57	22.81	21.24	19.92
SFA *Group*	63.45	37.23		88.76	28.46	21.44	35.54	32.87
SFA *Both*	59.4	38.77	75.91		29.61	23.13	34.54	33.25
DEA *All*	22.37	22.94	18.83	16.21		53.33	52.82	43.44
DEA *Years*	21.6	21	18.39	16.59	39.43		49.4	40.77
DEA *Groups*	19.97	20.99	14.22	12.16	37.6	30.92		60.97
DEA *Both*	17.74	18.68	14.16	12.73	41.42	29.09	57.5	

Notes: Upper right triangle denote the top 25% performers;
Lower left triangle denotes the bottom 25% performers.

also identified to be in the bottom quarter by SFA. Random chance alone would yield an expected value of 25% correspondence, while perfect correspondence gives a 100% level. Hence, a value of 22.37% indicates little consistency. While slightly better, the correspondence between DEA and SFA to identify top performers in the upper right triangle is again somewhat vague. Only after controlling for banking groups or both strata at the same time, both methods overlap in more than 25% of the cases in their identifications of top performers - clearly not very comfortable.

Within each class, this correspondence is higher compared to random sampling, but it is still far from perfect. Thus, different identifications of extreme performers are already subject to care within one methodology. The correspondence between DEA samples only is on average 50.12% for the best and 39.32% for the worst. In turn, the correspondence between SFA samples is 79.34% for the best and 56.08% for the worst.

In sum, the average correspondence between DEA and SFA to identify worst and best practice banks is 18.03% and 26.53%, respectively. Thus, the two methodologies do not identify extreme performers consistently. Given the higher with-in class stability of parametric methods, the latter may be taken as somewhat more reliable for policy-making purposes.

5.4 Stability Over Time

To be useful for regulatory policy purposes, efficiency measures should be stable over time. Just as the banking landscape in Europe is changing gradually, we expect that the efficiency rankings of banks do not exhibit large changes in the short run. In table 7 we therefore examine the year-to-year stability of DEA and SFA efficiency scores over time. We calculate for each method and sample rank order correlations between each pair of years.[13] Correlations are positive and significant at the 1% level in all cases. We summarize in table 7 the average correlations by the number of years apart.[14]

First, we find that efficiency rankings are more stable over time according to DEA but both methods yield consistently declining correlations over time. Since banking

[13] For example, for the full sample we compute rank-order correlations between efficiency in each year i between 1993 and 2003, and the full sample in each year j, j=1994,...,2004, with j>i. This

Table 7: Stability of efficiency over time

	Number of years between rankings										
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*
SFA *All*	87.1	80.8	76.1	72.0	68.6	65.3	62.9	61.1	59.1	56.6	55.2
SFA *Year*	67.0	60.0	54.8	49.6	50.8	54.6	53.1	49.0	41.9	32.3	24.5
SFA *Group*	88.0	82.2	77.6	73.6	70.3	66.9	63.8	61.8	58.9	55.5	52.2
SFA *Both*	85.9	79.5	74.6	70.3	67.2	64.0	60.7	58.4	57.1	55.7	54.5
DEA *All*	96.7	94.1	91.3	88.5	85.8	83.1	80.6	78.1	76.0	74.2	72.6
DEA *Years*	83.7	80.5	78.2	71.8	70.8	65.9	65.8	62.3	58.6	58.2	47.4
DEA *Groups*	94.7	91.9	89.2	86.4	84.0	81.5	79.2	76.9	75.3	74.2	73.8
DEA *Both*	87.1	81.5	76.5	71.9	69.2	63.2	60.9	58.6	56.9	55.9	49.0

All correlation coefficients are significant at the 1% level.

markets are competitive and dynamic environments, relative changes of efficiency rankings over time are reasonable, for example due to changing competitiveness. Note, however, that even after up to twelve 12 years later rankings are still quite highly correlated with initial ranks. Consequently, relative re-positioning in the banking industry regarding efficiency neither appears to occur quickly nor to a large extent.

Second, especially in the longer run a part of this trend may actually reflect different degrees of technical change across the various banking groups. Potentially, larger banks that are more exposed to international competition are more successful in adopting new technologies and products compared to regionally active banks. Obviously, such a conclusion requires more detailed analysis of technical change per bank and banking group over time and should be subject to future research.

Third, note that for both SFA and DEA rank instability is largest for annual samples. This result is most obvious when considering SFA efficiency measures with an interval of 11 years. Then, average rank-order correlations are only around 25%. This reinforces our previous statement about the time effect of SFA. The considerable gap to the other samples may be related to the commonplace assumption in the literature that bank production and cost are independent over time. In fact, non-parametric methods treat any observation in the data as independent by construction unless one specifies an explicit additional constraint in the linear programming set-up.[15] For DEA this result may therefore merely underpin a point made by Coelli et al. (1997): comparing efficiency measures measured relative to different (yearly) frontiers is subject to reservation. In the context of SFA, this result may in turn highlight the necessity to allow bank production choices to be autocorrelated or to follow a trend over time. Put differently, the ability of parametric methods to exploit the panel structure of micro-data with according estimators deserves attention for more than just technical reasons, but this succeeds the aim of our research.

In sum, rank stability over time is fairly high and statistically significant both

process was then repeated for the other 7 designs.

[14]Each number in the first column, for example, depicts mean correlation of efficiency in 1993 with 1994, 1994 with 1995,...,2003 with 2004, an average of 11 correlations in all. In general, the t-year apart figures are averages of 12 - t correlations between efficiencies that are t years away from each other.

[15]But, of course, an approach to constrain, say, relative future efficiency scores to always be smaller, equal or larger lacks any economic sensibility and is thus simply not feasible.

for DEA and, to a lesser extent, SFA. This result is especially strong in the short run and indicates a high consistency between methods. As for the other checks, the difference between DEA and SFA decrease with more homogenous samples.

5.5 Efficiency and Accounting-based Performance Measures

On the one hand, one may argue that efficiency measures should be positively correlated with alternative measures of performance commonly used by regulators and financial managers. On the other hand, the former are not necessarily based on microeconomic theory and are mostly directly based on accounting information. For example, high cost-income ratios may indicate poor cost management skills. However, they may just as well indicate that banking markets are highly competitive and, thus, marginal revenues are close to marginal cost.

Put differently, it is possible that efficiency scores contain additional information about performance compared to traditional measures. Therefore, we do not expect perfect correlation as the accounting ratios of performance do not consider input prices and output mix and ignore the market value of the bank (Berger and Humphrey, 1991). But if efficiency scores can indeed help to improve the performance evaluation of financial institutions we would expect the former to be at least significantly correlated with other performance indicators. Moreover, measures are more consistent if they indicate similar conclusions for policy-making purposes. Therefore, efficiency scores that are positively correlated with traditional measures may be regarded more informative than those that do not.

In table 8 we report correlation coefficients between both DEA and SFA efficiency scores and four non-frontier measures of performance. We chose two indicators of return performance as well as of cost performance of banks: return on assets (ROA) and return on equity (ROE); the negative of total operating cost to total assets (-TC/TA) and the negative of total cost to total revenue (-TC/TR). The negative signs are placed on the last two ratios so that all performance indicators should be positively correlated with efficiency scores.

Table 8: Consistency with standard performance measures

	SFA				**DEA**			
	All	*Years*	*Groups*	*Both*	*All*	*Years*	*Groups*	*Both*
ROE	12.7	11.0	21.1	19.8	6.6	15.0	21.8	16.6
ROA	10.5	9.3	11.9	11.6	2.4	7.2	9.0	10.4
TC/TA	31.6	14.3	40.4	33.7	11.7	7.4	30.1	30.9
TC/TR	21.0	14.3	26.1	23.9	5.7	8.0	19.8	19.6

All correlation coefficients are significant at the 1% level.

The results in table 8 suggest that neither parametric nor non-parametric efficiency measures are highly correlated with traditional performance measures. The low magnitude is in line with those reported by Bauer et al. (1998) and Koetter (2006) and confirm that efficiency measures contain additional information compared to traditional performance ratios. A popular empiricism is to cite return-on-asset or return-on-equity to compare the effectiveness of financial systems [16]. As the results prove, return indicators do not account for the efficiency characteristics of banks. Note that the consistency between cost efficiency and cost-related accounting measures is substantially higher compared to the relation to return oriented performance measures, such as ROE and ROA. Apparently, the ability to generate profits is captured by neither cost efficiency method well.[17] Since we are here mostly interested in the comparison between parametric and nonparametric methods, it is noteworthy that the similarity of information conveyed by SFA efficiency measures is by and large somewhat higher compared to that obtained with DEA. Moreover, the distinction in samples according to banking groups rather than years appears to explain much of the difference in performance rankings between traditional measures and cost efficiency. This is in line with results on mean efficiency in table 4. We conclude that especially the ability to control for systematic differences between different types of banks is important.

6 Conclusion

In this study we investigate the consistency of cost efficiency measures derived with two different methodologies: Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). To this end, we use an identical data set of universal banks in Germany reported to the Bundesbank between 1993 and 2004. We assess the sensitivity of SFA and DEA efficiency measures when the respective frontiers are based on an increasingly homogenous sample in terms of years and banking groups included.

Our main conclusions from the analysis of five consistency criteria are as follows. Mean cost efficiency levels are substantially higher according to SFA compared to those obtained with DEA. We identify two major reasons for this observations. First, since DEA uses a deterministic frontier to benchmark banks, the method is substantially more sensitive to the choice of banks included in the sample. When assessing the relative performance of Germany's fragmented three pillar system, higher heterogeneity in the data results in low mean efficiency because other factors influencing cost efficiency are not accounted for. We quantify the sensitivity of mean industry efficiency levels by constructing increasingly homogenous samples across years and banking groups and find in fact that SFA and DEA measures are very alike when comparing only banks of one group per year, respectively. Second, the parametric nature of SFA is found to be substantially less sensitive to outliers due to measurement error. While the exclusion of less than one percent of banks from the sample leads to an improvement in DEA scores of around 20 percentage points in terms of efficiency, SFA scores change only by 2 percentage points. Hence, if researchers have reason to believe that measurement error prevails, DEA should be used with care.

The analysis of efficiency rankings across methodologies and samples shows only limited evidence that both methods rank banks similarly. Only for the most re-

[16](White, 1998) uses measures on return to show the superiority of Anglo financial system over continental ones.

[17]This motivates to also consider profit efficiency in future studies as in Altunbas et al. (2001).

strictive samples per group and year, both measures exhibit rank-order correlations of around 44%. The limited extent to which the two methods identify the same institutes as best and worst performers is confirmed by comparing the overlap of the top and bottom 25^{th} efficiency percentile for each method and sample, respectively. Across all sample stratifications investigated here, the share of banks identified simultaneously as best and worst performers according to both methods is very low. We conclude that efficiency measures are only consistent if particular fractions of the banking market are analyzed. In turn, if the research interest is to benchmark the efficiency of a whole banking system the opportunity of SFA to account for random error and other non-random influences appears to render more stable efficiency information.

With respect to the stability of both methods over time we find despite ongoing changes in the industry during the last decade, such as consolidation and increasing competition, that both methods yield consistent rankings over time. In terms of cost efficiency, banks appear to perform equally good or bad in the course of time. The persistence of efficiency is markedly higher when measured with DEA compared to SFA, especially in the longer run. At the same time, both methods yield, in part, substantially lower time stability of rankings when using only yearly samples. Hence, efficiency methodologies like SFA, which are able to account for changes over time, are of particular importance beyond sheer technical reasons.

Regarding the relation of efficiency and traditionally employed accounting based measures, we conclude that either method yields efficiency measures that contain additional information. While positive correlations indicate that higher returns and lower costs move in lock-step with higher efficiency, low magnitudes indicate to us that accounting based measures do not fully capture alternative drivers of success and failure, such as market power or economic value maximization.

In sum, this study extends earlier findings for the US and sub-samples of other banking markets in Europe, which report differences between parametric and non-parametric efficiency scores. These differences apply also to other stability criteria and they are amplified when assessing the efficiency of an entire and large banking industry. It appears to be of crucial importance to control for heterogeneity over banking groups and time as well as for random noise and outliers.

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