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Measuring Performance

A Multiple-Stage Approach

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Abstract

In this paper we deal with the measurement of technical efficiency (or X-efficiency) of institutions whose operations might be significantly affected by macroeconomic, environmental and non-controllable factors. For this purpose we introduce a four-stage DEA methodology based on the approach advocated by Fried – Schmidt – Yaisawarng (1999) and advanced by Drake – Hall – Simper (2003), respectively. The latter approach improves upon the former by employing a slacks-based DEA model (SBM) in combination with a Tobit regression approach to account for potential environmental and market influences on technical efficiency. In order to cope with the inherent dependency problem of DEA-based efficiency scores when incorporated into regression analysis we propose a Bootstrap method as suggested by Xue – Harker (1999). In so doing we attempt to overcome the dependency problem which plagues the power of standard regression analysis based on DEA data. As illustration, we apply this four-stage model to a balanced panel of data of 729 Austrian banks ranging over 1995 to 2002.

JEL classification: F36,C23, C52, G21,G24,G34

Keywords: efficiency measurement, data envelopment analysis, slack adjustment, environmental variables, banking

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1. Introduction

The notion of frontier is at the heart of modern efficiency analysis. Methods built on this idea use frontier functions based on input-output relations to measure the (in-)efficiency of a so-called decision making unit (DMU) relative to these benchmarks. Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) are the two most principal methods used in the applied efficiency measurement literature. Both methods are aimed to measure technical efficiency only (remember, a DMU is said to operate technically efficient when it maximizes (minimizes) the output (input) from the given level of input (output)[1]).

In this paper we deal with the measurement of technical efficiency (or X-efficiency) of institutions whose operations might be significantly affected by macroeconomic, environmental and non-controllable factors. For this purpose we introduce a four-stage DEA methodology based on the approach advocated by Fried – Schmidt – Yaisawarng (1999) and advanced by Drake – Hall – Simper (2003), respectively. The latter approach improves upon the former by employing a slacks-based DEA model (SBM) in combination with a Tobit regression approach to account for potential environmental and market influences on technical efficiency. In order to cope with the inherent dependency problem of DEA-based efficiency scores when incorporated into regression analysis we propose a bootstrap method as suggested by Xue – Harker (1999). In so doing we attempt to overcome the dependency problem which plagues the inference power of standard regression analysis based on DEA data. We apply this four-stage model to a balanced panel of data of 729 Austrian banks ranging over 1995 to 2002.

The paper is organized as follows: Section 2 reviews the principal methods used in the applied efficiency measurement literature in a non-technical form. Section 3 introduces the four-stage DEA model aimed to account for environmental influences. Section 4 presents the results of the empirical application. Section 5 concludes.

2. Frontier Estimation Methodology

The methods of performance measurement we are going to discuss in this paper are the Stochastic Frontier Analysis (SFA) and the Data Envelopment Analysis (DEA). The former approach is parametric, the latter non-parametric. The basic DEA models used to estimate the frontier functions refer to the deterministic mathematical programming approach assuming that the observed data are neither random nor contaminated by measurement errors. The alternative approach SFA assumes the opposite by explicitly accounting for data noise. Consequently, statistical (or econometric) techniques are used as analytical tools. Other methods used in applied work but not surveyed in this paper are the Distribution Free Approach (DFA) and the Thick Frontier Approach (TFA), both of which are built on

[1]) As known, overall efficiency consists of four components: scale efficiency, scope efficiency, allocative efficiency and technical efficiency. Scale efficiency is given when the DMU operates at constant returns to scale. Scope efficiency occurs when the DMU chooses an input minimizing mix of outputs (products). A DMU is said to operate allocative efficiently when it chooses the revenue maximizing mix of outputs.

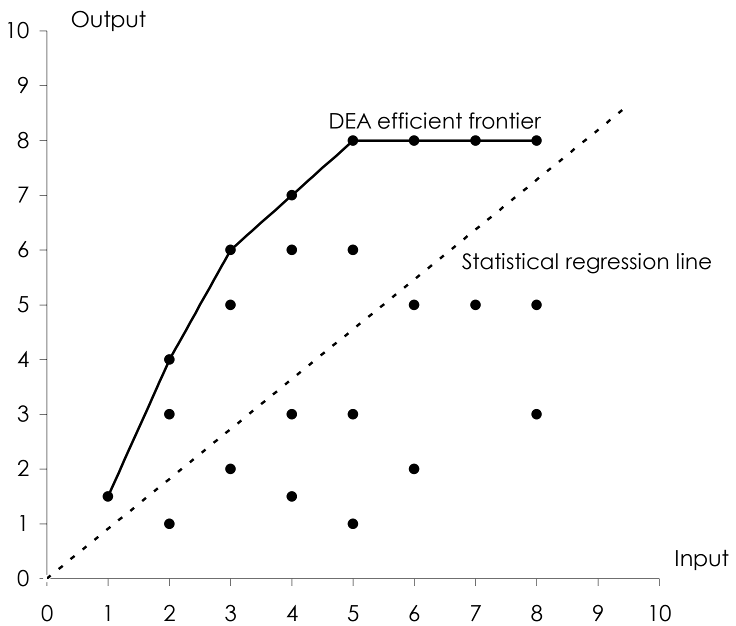
assumptions similar in spirit to the SFA. These methods differ mainly in their assumptions with respect to the shape of the efficient frontiers and in their treatment of random errors, respectively. For a competent review of the methods not discussed here, we refer the reader, inter alia, to Bauer – Berger – Humphrey (1998).

2.1 The Data Envelopment Analysis

Originally developed by Charnes – Cooper – Rhodes (1978), basic DEA applies deterministic mathematical programming techniques to observed input-output related data to reveal the efficient (best practice) frontier. Basic DEA is guided by the idea that the performance of DMUs (i.e., firms or non-profit institutions) is best estimated when one gauges their management's capability of minimizing input usage in the production of output (or vice versa) relative to the performance of other firms or institutions.

More formally, using multiple inputs and outputs the DEA techniques compute the technical efficiency of a DMU in relation to an estimated frontier surface. That is, the techniques employed are to uncover the closest fitting frontier which envelops all data points. To be efficient the DMU has to lie on this envelopment surface. Those DMUs that do not lie on this surface are termed inefficient. Thus, in contrast to parametric methods such as SFA, standard DEA does not account for data randomness. That is, no a-priori assumptions regarding the statistical distribution of the observed data points are required. This assumption concerning the data quality is considered to be one of the main deficiencies of the basic DEA models. The main advantage of DEA over SFA is that DEA models do not require a-priori assumptions with respect to the analytical form of the frontier (Figure 1).

Figure 1: Comparison of DEA and Regression Approaches



Source: Siems – Barr (1998).

In its simplest form, the DEA approach builds on the relative productive efficiency of a firm as measured by the ratio of its total weighted output to its total weighted input. By applying linear programming methods the DEA maximizes this ratio for each firm by putting higher weights on those inputs the firm uses least and those outputs the firm produces most (Siems-Barr, 1998).

The most basic DEA model has been pioneered by Charnes – Cooper – Rhodes (1978), since then known as CCR model. It is an input-oriented, constant returns to scale (CRS) model where for each firm or DMU, an efficiency measure is obtained by defining the ratio of all outputs over all inputs, that is, $\frac{u' y_O}{v' x_O}$ with y_O denoting the output vector of the $o-th$ firm and x_O the input vector, respectively. The output and input weights are denoted by u and v, respectively.

The optimal weights of the DMU_O, where o ranges over $1, 2, \ldots\ldots, n$ are gained by solving the linear mathematical programming problem (1):

$$
\begin{aligned}
\max_{u,v} \quad & \theta = \sum_{i=1}^{s} u_i y_{iO} \\
\textit{subject to} \quad & \sum_{j=1}^{m} v_j x_{jO} = 1 \\
& \sum_{i=1}^{s} u_i y_{i,k} \le \sum_{j=1}^{m} v_j x_{j,k} \\
& (k = 1, \ldots\ldots, n) \\
& v_1, v_2, \ldots\ldots, v_m \ge 0 \\
& u_1, u_2, \ldots\ldots, u_s \ge 0
\end{aligned}
\tag{1}
$$

The linear program (1), called the multiplier form, is equivalent to the fractional programming problem which focuses on maximizing the ratio of weighted outputs over all weighted inputs of the DMU_O. Designing the maximization problem as a linear programming exercise has the advantage of avoiding the nuisance of an infinite number of solutions which plagues the fractional programming approach. In the applied literature the preferred form of the DEA programming problem is the dual form of the linear program (1) because of the computational ease due to fewer constraints. The relative efficiency scores are bounded by zero (lowest level of efficiency) and unity (highest level of efficiency).

2.2 The Stochastic Frontier Analysis

The SFA deals with the problem that not all deviations from the frontier may be due to inefficiency. Deviations from the benchmark may also occur due to bad (or good) luck or measurement errors. Aigner – Lovell – Schmidt (1977) address this problem by proposing a stochastic frontier model with a random disturbance term. This term is designed as the sum of two random components where the one is symmetrically distributed around zero capturing measurement errors and unobservable shocks and the other is strictly negative measuring inefficiency. The basic SFA model has the following form:

$$y_i = f(x_i;\beta) + u_i + v_i \tag{2}$$

with y_i denoting the output of the $i-th$ DMU, $f(x_i;\beta)$ is the production function with x_i representing the input vector and β the unknown parameter vector, v_i stands for the symmetric and u_i for the negative random term, respectively. The disturbance term v_i is assumed to be independently and identically distributed (iid) normal with zero mean and σ_v standard deviation, i.e., $N(0,\sigma_v^2)$. Though also iid and independently generated from v_i the inefficiency term u_i is supposed to follow a statistical distribution allowing for $u_i \leq 0$ such as, for example, the truncated normal distribution or the exponential distribution. Jondrow et al. (1982) show that the X-inefficiency of firm i can be expressed as the expected value of u_i, conditional on $\varepsilon_i = u_i + v_i$.

The main shortcomings of SFA are its high vulnerability to outlying observations and the rather arbitrary choice of the distributional assumption regarding the inefficiency component of the error term (see for a discussion of these topics, for example, Wagenvoort – Schure, 1999).

3. Considering the Environment – A Multiple-Stage Procedure

3.1 An Overview

In the respective literature various ways are discussed concerning the proper account of the impact of external variables when measuring firm efficiency (see for an introduction to this topic, i.e., Coell – Prasada Rao – Battese, 1998). In the DEA oriented efficiency measurement literature the two-stage approach is the most prominent. This approach uses the relative efficiency measure computed by a DEA model as the dependent variable in a second stage regression with the explanatory variables supposed to capture the impact of the external factors. Though this approach allows for testing the influence of external factors in terms of sign and significance it ignores the information contained in the input slacks and output surpluses. Consequently, this procedure does not provide an empirical technique to separate the management component of inefficiency from the external components.

Fried – Schmidt – Yaisawarng (1999) introduce an extension of the two-stage model aimed at obtaining a measure of the management component of inefficiency exempt from the influences of external or environmental factors. Only a pure measure of managerial inefficiency allows for comparing the performance of managers across firms because only in rare cases do firms operate under the same external regimes. In order to isolate the internal factors Fried – Schmidt – Yaisawarng (1999) propose the following four-stage procedure. First, a DEA frontier based on the traditional input-output relation according to the standard production theory is computed (Fried – Schmidt – Yaisawarng, (1999), suggest a variable returns-to-scale DEA model, known as BCC-model since it has been introduced by Banker –

Charnes – Cooper, 1984). Second, depending on model specification the input slack (or the output surplus) is used as dependent variable in a regression analysis approach with a set of external factors as regressors measuring the relevant features of the external environment the DMUs are operating in. Third, these parameter estimates are used to adjust the input slacks or output surpluses of the DMU so that the adjusted values represent the allowable slack or surplus due to the operating environment (Fried – Schmidt – Yaisawarng, 1999). In the finale stage the initial data is reassessed according to the calculations in the third stage and the initial DEA model is re-estimated on the basis of the adjusted data set.

Put differently, this procedure is aimed at adapting the external conditions of the DMUs in the sense that the environmental factor is no longer substantial in terms of managerial inefficiency. As a result, a new frontier can be computed which is (or is supposed to be) free from environmental influences and better qualified to measure the pure managerial component of inefficiency.

Drake – Hall – Simper (2003) improve upon this approach by using a slacks-based DEA model (SBM) introduced by Tone (2001). This alternative DEA model has two important properties which lack standard DEA: First, the relative efficiency measure gained by this model is invariant with respect to the unit of measurement of each input and output item, and second, the efficiency measure is monotone decreasing in each input and output slack (Cooper –Seifried – Tone, 2000). That is to say, the SBM deals with input excesses and output shortfalls directly by incorporating the information contained in the slacks into the objective function. No matter what the scale of the measurement the SBM generates a representative measure able to gauge the depth of inefficiency by reflecting nonzero slack in inputs and outputs when they are present.

An inherent property of all DEA models is that all measures generated by these models are dependent on each other in the statistical sense. This critical point has been recently raised by Xue – Harker (1999). The authors argue that the dependency property triggers a serious setback when the DEA efficiency measures such as the scores or the slacks are used in standard regression analysis to explain the variations of these measures. Because the DEA measures violate the assumption of independence within the sample, statistical inference is impaired when standard regression techniques are applied without controlling for this constraint. Thus, conclusions reached on the basis of standard regression analysis may be flawed since given dependency of the response variable the standard errors of the regression coefficient estimates are no longer correct. That is, the $t-$ratios and the $p-$values for the hypothesis tests are very likely to be severely biased.

This unpleasant consequence of the inherent dependency problem of the DEA has been long ignored in the literature. As a possible tool to fix this problem in the non-parametric analysis of the DEA Xue – Harker (1999) suggest the Bootstrap method. We follow this recommendation and apply the Bootstrap to the multiple stage procedure introduced by Fried – Schmidt – Yaisawarng (1999) and Drake – Hall – Simper (2003), respectively. A similar approach to overcome the dependency problem in a two-stage framework has been chosen by Casu – Molyneux (2003).

3.2 The Formal Procedure

The proposed multiple-stage procedure for measuring the pure managerial inefficiency consists of the following phases:

Phase 1: Computing the frontier

The DEA model proposed to compute technical efficiency is the input-oriented SBM due to Tone (2001). The basic SBM is a linear mathematical program with the following structure:

$$\begin{aligned}
\min_{t,\lambda,s^-,s^+} \quad & \tau = t - \tfrac{1}{m}\sum_{i=1}^{m}\frac{S_i^-}{x_{io}} \\
\textit{subject to} \quad & 1 = t + \tfrac{1}{s}\sum_{r=1}^{s}\frac{S_r^+}{y_{ro}} \\
& tx_o = \mathrm{X}\Lambda + S^- \\
& ty_o = \mathrm{Y}\Lambda + S^+
\end{aligned} \tag{1*}$$

with $\mathrm{X} = (x_{ij}) \in \Re^{m\times n}$, $\mathrm{Y} = (y_{ij}) \in \Re^{s\times n}$ representing the set of inputs and outputs, respectively, $S^- = ts^- \geq 0,\ S^+ = ts^+ \geq 0,\ \Lambda = t\lambda,$ where t is a positive scalar variable and $\lambda \in \Re^n$, s^-, s^+ denote the total (that is, radial and non-radial) input and output slack vectors defined as $x_o = \mathrm{X}\lambda + s^-$ and $y_o = \mathrm{Y}\lambda + s^+$, respectively[2]).

Phase 2: Estimating the slack equations by Bootstrap

Since the response variables generated by DEA models are censored by nature, estimating the slack equations with external factors as regressors requires an appropriate econometric technique. We consider the Tobit censored regression model to be appropriate in the given context. Given the DEA is input-oriented the objective is to quantify the effect of the environmental factors on the excessive use of inputs. That is, we estimate the following m input slack equations

$$ITS_j^k = f_j(Q_j^k, \beta_j, v_j^k), \qquad k = 1,.....,n \quad j = 1,......,m \tag{2*}$$

where ITS_j^k represents the $k-th$ DMU's total slack for input j as calculated by a DEA model such as (1^*), Q_j^k is a vector of variables capturing the influence of the operating

2) For a definition and related illustration of radial and non-radial input slack, see Fried – Schmidt – Yaisawarng (1999), Figure 1.

environment of DMU k on the usage of input j, β_j is the vector of parameters to be estimated and v_j^k is the disturbance term.

The Bootstrap

According to Xue – Harker (1999) we apply the Bootstrap method to overcome the inherent dependency of the m input slack variables ITS_j^k. The proposed Bootstrap procedure introduced by Efron – Tibshirani (1993) has the following general structure:

Step 1: Construct the sample probability distribution $\hat{F}$ by assigning probability of $1/n$ at each DMU in the observed sample: $(x_1, x_2, ..., x_n)$.

Step 2: Draw c (c is a constant) random samples of size n with replacement from the original sample $(x_1, x_2, ..., x_n)$:

$$S_k = (x_{k1}, x_{k2}, ..., x_{kn}), \quad k = 1, ..., c,$$

where $x_{ki} = (u_{ki}, v_{ki})$, $i = 1, ..., n.$ S_k is the so-called Bootstrap sample.

Step 3: For each Bootstrap sample S_k, $k = 1, ..., c,$ run the DEA model and re-calculate the efficiency scores and slacks for all n DMUs:

$$\theta_{kj} = \phi_i(u_k), \quad i = 1, ..., n,$$

where ϕ_i represents the DEA model for DMU i.

Step 4: For each Bootstrap sample $S_k = (x_{k1}, x_{k2}, ..., x_{kn})$, $k = 1, ..., c,$ evaluate the Bootstrap replication $\hat{\beta}_{kj}$, $k = 1, ..., c,$ $j = 0, 1, ..., m$ by fitting the regression model:

$$\theta_{ki} = G(\beta_k, v_{ki}) + \varepsilon_{ki}, \quad i = 1, ..., n,$$
$$\beta_k = (\beta_{k0}, \beta_{k1}, ..., \beta_{kj}, ..., \beta_{km})$$

Step 5: Estimate the standard error $se(\hat{\beta}_j)$ by the sample standard deviation of the c Bootstrap replications of $\hat{\beta}_j$:

$$\hat{se}_c\left(\hat{\beta}_j\right)=\left\{\frac{\sum_{k=1}^{c}(\hat{\beta}_{kj}-\overline{\beta}_j)^2}{(c-1)}\right\}^{\frac{1}{2}}, \quad j=0,1,....,m,$$

where

$$\overline{\beta}_j=\frac{\sum_{k=1}^{c}\hat{\beta}_{kj}}{c}, \quad j=0,1,.....,m.$$

The term $se\left(\hat{\beta}_j\right)$ is called the Bootstrap estimator for the standard error of $\hat{\beta}_j$.

Step 6: Test the following hypothesis by applying a $t-$Test:

$$t=\frac{\hat{\beta}_j}{\hat{se}_c\left(\hat{\beta}_j\right)} \quad ,$$

and compare t to the critical value $t_{\alpha/2}$ from the student t distribution with degrees of freedom equal to $(n-m-1)$.

Phase 3: Adjusting primary data for the influence of external conditions

The estimated coefficients of equation (2^*) are used to calculate the prediction value of the total input slack for each input and for each DMU based on its external factors:

$$I\hat{T}S_j^k=f_j\left(Q_j^k,\hat{\beta}_j\right), k=1,.....,n \quad j=1,.....,m \tag{3*}$$

Based on these predictions the primary inputs for each DMU are adjusted according to the difference between maximum predicted slack and predicted slack:

$$x_j^{k\,adj}=x_j^k+[\max^k \{I\hat{T}S_j^k\}-I\hat{T}S_j^k], \quad k=1,......,n \quad j=1,......,m \tag{4*}$$

These input adjustment equations establish an equal base for all DMU concerning their non-controllable surroundings. Obviously, the chosen adjustment mechanism is designed to generate an identical pseudo environment which is to be the least favorable for all DMUs. Needless to state, the opposite adjustment mechanism (that is, the firms are assumed to operate under the most favorable external circumstances) works as well and leads to the same results.

Phase 4: Re-run the DEA model using the adjusted primary data set

Model (1^*) is re-run based on the adjusted input data set according to the equation system (4^*). This generates new radial scores which are capable of measuring the inefficiency which is attributable to management.

4. Measuring Banking Performance in Austria – First Results

As illustration, we apply the multiple-stage approach outlined in section 3 to a sample consisting of a balanced panel of annual report data of 729 Austrian universal banks (unfortunately, access to quarterly or monthly data was not made possible). The bank data were extracted from non-consolidated income statement and balance sheet data ranging over 1995 to 2002. The data set has been drawn from the electronic databank of the Oesterreichische Nationalbank (OeNB).

A still unresolved problem in the banking performance literature is the definition and measurement of the concept of bank output (and, of course, bank input). We do not dwell on this important question in this paper and refer the interested reader to Berger – Mester (2003) for a competent treatment of this topic. Instead, we follow the argumentation of Berger – Mester (2003) and Drake –Hall – Simper (2004), respectively, and employ a profit-oriented approach rather than the usual 'intermediation', 'production', or 'value added' specifications. According to Berger – Mester (2003) the profit approach seems to be better qualified to capture the ongoing changes towards higher quality services in banking and the stronger profit-orientation of the banks' management observable since the beginning of the 1990s. Thus, we specify cost components as inputs such as employee expenses, other non-interest expenses and risk-weighted assets as measured by Basel I. The latter input variable is supposed to account for a bank's financial risk exposure which might have a significant impact on relative efficiency scores. The argument is that higher financial risk exposure is likely to elevate the bank's cost of funds (see, for example, Akhigbe – McNulty, 2003). However, it might also be the case that financial risk increases the pressure on the management to improve upon efficiency. The output variables consist of the following revenue components: net interest revenue, net commission revenue, and other income[3]. A summary data description is given in Table 1. The Data Appendix gives the details on the definition of the variables and the data sources, respectively.

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3) All input and output variables are deflated by GDP deflator, 1995 = 100.

Table 1: Summary Data Description – Balanced Sample of 729 Austrian Banks

	Input variables			Output variables		
	Employee expenses	Non-interest expenses	Risk-weighted assets	Other income	Net interest revenue	Net commission revenue
1995						
Minimum	0,0	0,0	0,0	-3,0	-2,0	-9,2
Maximum	122,3	60,9	7.650,8	43,3	191,1	41,7
Mean	2,4	1,2	114,0	0,3	4,3	1,0
Standard deviation	7,4	4,1	469,4	2,2	12,6	3,6
1996						
Minimum	0,0	0,0	0,0	-14,0	-5,2	-4,9
Maximum	125,9	59,9	7.977,5	42,1	214,2	49,6
Mean	2,4	1,3	117,9	0,3	4,3	1,1
Standard deviation	7,4	4,2	496,4	2,4	13,3	3,9
1997						
Minimum	0,0	0,0	0,0	-7,1	-5,7	-7,7
Maximum	129,4	60,0	9.264,6	44,2	223,0	63,5
Mean	2,4	1,4	124,1	0,3	4,2	1,2
Standard deviation	7,5	4,6	534,5	2,5	13,3	4,5
1998						
Minimum	0,0	0,0	0,1	-18,5	-2,8	-10,6
Maximum	135,9	70,0	10.001,9	49,7	221,2	65,7
Mean	2,5	1,5	133,5	0,3	4,2	1,4
Standard deviation	7,9	5,0	589,0	2,6	13,2	5,0
1999						
Minimum	0,0	0,0	0,2	-53,4	-3,0	-15,4
Maximum	143,6	80,6	11.558,9	60,6	241,3	70,2
Mean	2,6	1,5	145,7	0,2	4,2	1,6
Standard deviation	8,3	5,2	676,4	3,4	13,9	5,6
2000						
Minimum	0,0	0,0	0,4	-2,7	-3,9	-22,8
Maximum	153,2	87,0	13.187,3	71,2	257,6	88,5
Mean	2,7	1,6	158,2	0,3	4,5	1,8
Standard deviation	8,7	5,5	775,1	3,0	14,2	6,5
2001						
Minimum	0,0	0,0	0,2	-0,4	-3,9	-27,3
Maximum	157,1	96,5	17.714,3	79,6	283,3	103,9
Mean	2,7	1,8	176,5	0,4	4,5	1,8
Standard deviation	8,8	6,3	964,3	3,9	15,5	6,9
2002						
Minimum	0,0	0,0	0,3	-1,2	-4,3	-29,0
Maximum	163,7	93,2	17.682,7	78,5	273,8	115,0
Mean	2,8	1,8	184,6	0,3	4,7	1,7
Standard deviation	9,1	6,1	996,5	3,4	16,0	7,0

Source: OeNB, own calculations; minimum, maximum and mean as mn €.

For illustrative purposes, we assume that the size of a bank is a sufficiently good proxy for its specific market environment[4]). Large banks usually operate nationwide or even internationally and, thus, face a different market environment than the regional or local banks. Large banks provide, to a great extent, more advanced banking services such as investment banking and wholesale banking. This is done under an external environment which is highly competitive. Regional banks are mostly medium-sized and operate under market conditions which are basically determined by factors such as the strong inclination of regional banks' customers towards retail banking products, low profile investment banking services and liquidity availability. The latter service is primarily provided to medium-sized businesses and state governments, respectively. In addition, regional banks often enjoy the luxury of working a market which allows for some monopoly powers due to the close relationship with their clientele. Finally, local banks do operate, with no exception, on a small scale basis and serve mainly a clientele, consisting of low income families and small business owners, that demands standard retail banking products only. Local banking is primarily relationship-based and allows local banks, to a much greater extent than regional banks, to act as local monopolists. For the definition of large-sized, medium-sized and small-sized banks the reader is referred to the Data Appendix. Only 24 Austrian banks can be considered to be large in national terms, all of which operate on a nationwide and/or international basis. The rest of the sample is divided in 394 small-sized and 311 medium-sized banks.

According to our formal procedure, we first calculate the efficiency scores without incorporating environmental factors for our sample of 729 Austrian banks on the basis of an input-oriented, variable returns-to-scale SBM model[5]). The period of analysis ranges from 1995 to 2002. A summary of the efficiency results is reported in Figure 2 and reveals a rather high degree of inefficiency. The scores range from 0.694 (1995) to 0.448 (2001). The low levels of efficiency are not uncommon in bank efficiency studies which do not account for environmental factors. Note that the profit-oriented scores follow a pattern over time which strongly parallels the underlying overall business cycle (this finding is mainly due to the profit-orientation of the chosen DEA model). Obviously, banking efficiency in Austria takes a nosedive whenever a downturn slows the overall economy. During the years of high economic growth banking efficiency seems to run high.

In a second step we try to account for various environmental factors which are closely linked to the size of a bank. For this purpose, we divide the data sample, as outlined above, into three groups: large banks, medium banks and small banks and run Tobit-censored regressions, accordingly, with the slacks of the cost components 'employee expenses', 'other non-interest expenses' and 'risk-weighted assets, as measured by Basel I', as the dependent variables.

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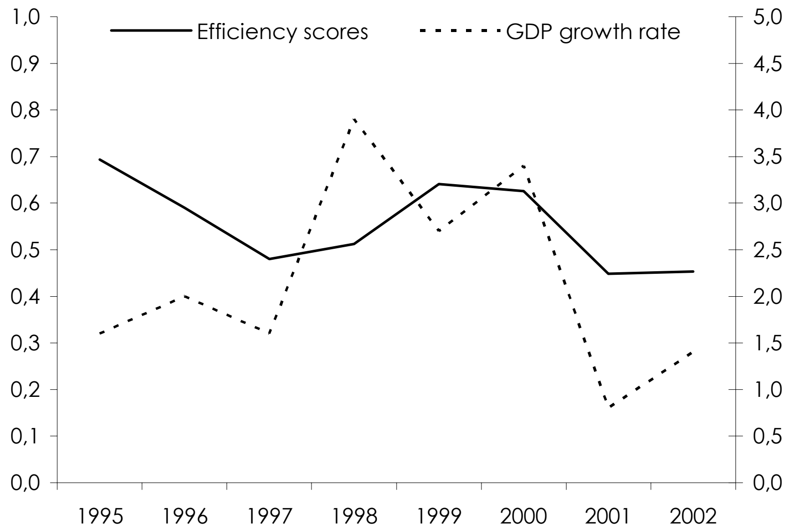
[4]) In a paper soon to be presented we report the results of an analysis of a broad set of external variables. The used external factors are supposed to give a much more precise picture of the market environment Austrian banks had to cope with over the period 1995 to 2002.

[5]) The relative efficiency scores and the related input slacks were obtained from the DEA Solver Professional Program due to Cooper – Seifried – Tone (2000).

Figure 2: Non-environmentally Adjusted Efficiency Scores over the Business Cycle
Average scores of the Austrian Banking Sector



Since the results of the Tobit regressions did not differ significantly from those of the Bootstrap estimators with c=1000 we take the Tobit estimates to adjust the inputs for the environmental bias due to the very factors which correlate with the size of a bank. As illustration, we report the Tobit regressions results of the three slack equations for the year 1997 in Table 2.

Table 2: Slack Equations – Tobit Regression Results for 1997
SBM Stage 1 Total Input Slacks

	Employee expenses		Non-interest expenses		Risk-weighted assets	
Large banks	5.177	***	3.566	***	236.768	***
	(0.313)		(0.378)		(18.589)	
Medium banks	1.496	***	0.763	***	37.777	***
	(0.082)		(0.098)		(4.453)	
Small banks	0.225	***	0.112	***	4.448	
	(0.079)		(0.095)		(4.286)	
Sigma	1.514	***	1.806	***	89.271	***
	(0.041)		(0.049)		(2.539)	
Log-Likelihood	-1,307.8		-1,422.3		-3,814.4	

*** ... significant at the 1% critical level; standard errors in parentheses.

In the final step, we re-run the initial SBM model using the adjusted instead of the original input variables. The initial and new efficiency scores are reported in Table 3. Most importantly, controlling for the impact of environmental factors elevates the average efficiency over the period of analysis significantly. The average efficiency level of the entire Austrian banking sector for the period 1995 to 2002 runs as high as 0.74 after controlling for the size-related environments of the Austrian banks (average efficiency level based on initial inputs: 0.56). In addition, the two efficiency estimates seem to have little in common, they are only weakly correlated with each other (Table 3, last column). However, the new results also indicate that the size of a bank doesn't matter in terms of its efficiency achievements over the business cycle. The new efficiency scores co-move at least as strongly with the business cycle fluctuation as the scores of stage 1.

Due to the preliminary value of the computations we refrain from further interpretation of the results. More founded estimates will be presented soon.

Table 3: Austrian Banking Sector – Initial versus Adjusted Efficiency Scores
Average Scores of all Banks

	Initial efficiency scores		Adjusted efficiency scores		Correlation coefficient[1])
	Mean	Standard deviation	Mean	Standard deviation	
1995	0,6939	0,1361	0,8325	0,0966	0,2105
1996	0,5903	0,1377	0,8376	0,1054	0,3317
1997	0,4799	0,1578	0,7070	0,1138	0,4663
1998	0,5122	0,1487	0,7320	0,0880	0,4544
1999	0,6407	0,1494	0,8726	0,0721	0,5502
2000	0,6257	0,1495	0,8515	0,0777	0,5051
2001	0,4483	0,1386	0,6327	0,0750	0,5651
2002	0,4533	0,1348	0,4503	0,1010	0,5865

[1]) Correlation between initial efficiency scores and adjusted efficiency scores.

5. Conclusion

In this paper we presented an efficiency measurement procedure which is fit for controlling for environmental factors affecting the efficiency of firms or institutions. The procedure combines DEA with regression analysis to explain the variations of managerial inefficiency. In order to cope with the inherent dependency problem of DEA-based efficiency scores when incorporated into regression analysis a Bootstrap estimator is applied as suggested by Xue – Harker (1999). As illustration, we applied this four-stage model to a balanced panel of data of 729 Austrian banks ranging over 1995 to 2002. The calculations show that controlling for the impact of environmental factors increases the average efficiency level over the period of analysis significantly. The average efficiency level for the period 1995 to 2002 when controlling for the size-related environments runs as high as 0.74 compared to 0.56 without accounting for external factors. The two efficiency estimates have little in common, they are only weakly correlated with each other. However, the results also indicate that the size of a bank doesn't matter in terms of its efficiency achievements over the business cycle. The size-adjusted efficiency scores co-move at least as strongly with the business cycle as the initial scores.

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Data Appendix: Variables and Sources

Variable	Definition	Original source
Employee expenses (mn. €)	Position code: 0040000	OeNB, Annual Reports Statistics of Austrian Banks
Non-interest expenses (mn. €)	Position code: 0050000	OeNB, Annual Reports Statistics of Austrian Banks
Risk-weighted assets (mn. €)	Position code: 4150500	OeNB, Annual Reports Statistics of Austrian Banks
Other income (mn. €)	Position code: 0806000	OeNB, Annual Reports Statistics of Austrian Banks
Net interest revenue (mn. €)	Position code: 1800000	OeNB, Annual Reports Statistics of Austrian Banks
Net commission revenue (mn. €)	Position codes: 030100-030200	OeNB, Annual Reports Statistics of Austrian Banks
GDP-deflator	1995 = 100	WIFO data base

Small banks	Banks within the interval ranging from the minimum to the median of total asset of the entire sample
Medium banks	Banks within the interval ranging from the median to the mean plus 1 quarter of the standard deviation of total asset of the entire sample
Large banks	Banks within the interval ranging from the mean plus 1 quarter of the standard deviation to the maximum of total asset of the entire sample

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