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Environmental Determinants of Banking Efficiency in Austria

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Abstract

The great majority of Austrian banks operate on a regional or local basis and only a few banks provide their services on a national or even international scale. Obviously, the market environments regional or local banks face are different from that of nationwide operating banks. Casual evidence suggests that local markets condition is a very important external determinant of banking efficiency. Thus, not controlling for market conditions may substantially bias the measurement of managerial efficiency particularly of locally operating banks. In this paper we assess the internal technical efficiency (or X-efficiency) of the Austrian banking sector with the focus on environmental and non-controllable factors critical to banking markets. Analytically, we apply a multiple-stage approach based on a slacks-based DEA model (SBM) and a censored regression model, respectively. In order to cope with the inherent dependency problem of DEA-based efficiency analysis when incorporated into regression analysis we apply a Bootstrap estimator. In so doing we attempt to overcome the dependency problem which plagues the power of standard regression analysis based on DEA processed data. The empirical analysis is based on an unbalanced panel of data covering more than 800 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

In this paper we assess the level of technical efficiency (or X-efficiency) of the Austrian banking sector with the focus on environmental factors affecting banking efficiency. For this purpose we use 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 processed data. We apply this four-stage model to an unbalanced panel of data of more than 800 Austrian banks ranging over 1995 to 2002.

The paper is organized as follows: Section 2 introduces the four-stage DEA model aimed to account for environmental influences. Section 3 presents the results of the empirical analysis. Section 4 concludes.

2. Considering Environmental Factors in Efficiency Analysis – A Multiple-Stage Approach

2.1 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., *Coelli – 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 Tobit-censored 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 freed of 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[1]). 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 under investigation are operating in. Third, these parameter estimates are used to adjust the input slacks or output surpluses of the DMUs 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 critical in terms of biasing managerial inefficiency. As a result, a new frontier can be computed which is (or is supposed to be) free of environmental interferences 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 long been ignored in the literature. *Xue – Harker* (1999) suggest the Bootstrap method to mitigate the inference fallout of the DEA dependency problem. We follow this recommendation and apply the Bootstrap to the multiple-stage procedure introduced by *Fried – Schmidt –*

1) *Fried – Schmidt – Yaisawarng* (1999) suggest a variable returns-to-scale DEA model, known as BCC-model in reference to *Banker – Charnes – Cooper* (1984).

Yaisawarng (1999). A Bootstrap estimator to overcome the dependency problem in a two-stage framework has also been applied by *Casu – Molyneux* (2003).

2.2 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). In the most general form, the SBM has the following structure:

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

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]). Note that input-orientation requires that the scalar variable t be set equal one.

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

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

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

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 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:

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

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

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

These input adjustment equations establish an equal base for all DMUs 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.

3. Banking Efficiency Subject to External Markets Condition: Evidence from Austria

We apply the multiple-stage approach outlined in section 2 to a sample consisting of an unbalanced panel of annual report data of more than 800 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). The output variables consist of the following revenue components: net interest revenue, net commission revenue, and other income[3]).

To check the robustness of the regression analysis based on the profit-oriented approach, we additionally apply the intermediation approach which views financial institutions as mediators between the supply and the demand of funds. Following *Casu – Molyneux* (2003) we specify an intermediation-oriented model that consists of two outputs (total loans, other earnings) and two inputs (total costs covering interest expenses, non-interest expenses, and employee expenses, respectively, and total deposits)[4]).

Table 1 shows some descriptive statistics of the bank sample as used in the profit-oriented model. 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.

[4]) Data and results of the intermediation-related model are not reported but made available on request.

Table 1: Summary Data Description – Unbalanced Sample of Austrian Banks

		Input variables			Output variables		
		Employee expenses	Non-interest expenses	Risk-weighted assets	Other income	Net interest revenue	Net commission revenue
1996	Observations: 1,007						
	Minimum	0.0	0.0	0.0	-14.0	-5.2	-4.9
	Maximum	559.2	305.3	29,883.6	101.9	891.5	214.4
	Mean	3.9	2.3	199.6	0.6	6.5	1.9
	Standard deviation	24.2	14.5	1,418.7	5.3	37.6	11.2
1997	Observations: 982						
	Minimum	0.0	0.0	0.0	-18.8	-5.7	-7.7
	Maximum	543.3	281.7	32,952.7	98.1	823.7	227.4
	Mean	4.1	2.4	220.2	0.6	6.4	2.1
	Standard deviation	25.5	15.1	1,666.9	5.5	38.0	12.7
1998	Observations: 952						
	Minimum	0.0	0.0	0.0	-18.5	-2.8	-10.6
	Maximum	588.6	261.4	30,967.6	130.1	800.9	247.1
	Mean	4.3	2.6	231.7	0.6	6.4	2.4
	Standard deviation	26.0	15.3	1,521.0	6.2	35.8	13.9
1999	Observations: 929						
	Minimum	0.0	0.0	0.0	-53.4	-3.0	-15.4
	Maximum	679.8	313.1	33,875.8	90.5	719.6	257.7
	Mean	4.5	2.8	260.0	0.5	6.4	2.7
	Standard deviation	27.6	16.3	1,696.2	5.4	33.7	14.6
2000	Observations: 896						
	Minimum	0.0	0.0	0.0	-2.7	-3.9	-22.8
	Maximum	698.4	351.7	38,779.4	93.0	754.3	324.6
	Mean	4.7	3.0	278.8	0.5	7.0	3.2
	Standard deviation	28.6	18.4	1,834.6	4.7	37.1	17.2
2001	Observations: 881						
	Minimum	0.0	0.0	0.0	-1.8	-20.2	-27.3
	Maximum	765.8	334.1	36,570.8	79.6	764.7	292.1
	Mean	4.8	3.3	302.1	0.5	7.3	3.2
	Standard deviation	30.8	18.7	1,908.0	5.1	38.6	17.0
2002	Observations: 872						
	Minimum	0.0	0.0	0.2	-1.2	-20.7	-29.0
	Maximum	994.9	547.5	50,383.7	138.1	1,171.3	551.1
	Mean	4.9	3.3	305.6	0.6	7.2	3.2
	Standard deviation	36.7	21.4	2,137.1	6.2	44.6	21.3

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

The great majority of Austrian banks operate on a regional or local basis and only a few banks provide their services on a national or even international scale. Obviously, the market environments regional or local banks are facing are different from that of nationwide operating banks. Casual evidence suggests that local markets condition is a very important external determinant of banking efficiency. Thus, not controlling for market conditions may substantially bias the measurement of managerial efficiency particularly of locally operating banks. Consequently, we try to control for environmental factors which are assumed to be critical to determining local markets conditions. Since less than 10 percent of the Austrian universal banks entertain operation units outside of the regional district of their headquarters we conclude that the very region where the bank is located provide a good basis for the approximation of the home or local market condition of the banks under study. The definition of a regional district is identical with that of an Austrian administrative district, a geographic unit just below the NUTS-III level of EUROSTAT[5]). Due to lack of banking environment-related data on a local or regional basis we use income per capita of these districts as an indicator for the local demand structure that might determine banking services supply. In so doing, we divide the 99 Austrian administrative districts into 5 groups, ranging from low income regions (BRPK 1) to high income regions (BRPK 5), each of which defined as a discrete and binary variable. That is, the income group variable is set to 1 when the bank is headquartered in a district which belongs to this income group and set to 0 otherwise. Technical details on the definition of this variable and on the data source, respectively, are given in the Data Appendix.

The chosen data grouping rests on the assumption that the level of income per capita, by determining the structure of demand for banking services, determines to a large extent the markets condition for banks. For example, as compared with low-income customers a high-income clientele is expected to show both, a higher demand for advanced banking services such as investment banking products and a higher product quality awareness. Further, high-income districts are more likely to be economically more developed than low-income regions which again results in higher demand for wholesale banking products in the former and for retail banking products in the latter. Thus, the expectation is that banks which primarily operate in richer districts face an external environment which is likely to foster banking efficiency. Meeting the sophisticated demands of a wealthy clientele ought to call for the employment of high-quality personnel and of state-of-the-art information and communication processing technology, respectively, both of which certainly propels banking efficiency. Conversely, banks doing business in less advanced and poorer regions are expected to be less efficient due to external conditions which hamper managerial excellence. Banks in rural areas mostly serve a low- to middle-income clientele with a strong preference for standardized retail banking products. As a result, the professional qualifications of the employees and the state of technology in rural banks are likely to be of lower order than in urban banks. We tend to consider the latter as one of the most compelling reasons why internal banking efficiency in rural areas may be expected to drag behind internal banking efficiency in urban regions.

In addition, we also apply our approach to a data sample grouped according to a regional classification that goes back to *Palme* (1995). The author classifies the Austrian administrative districts by their economic structures using multivariate cluster analysis. This classification scheme results in 9 economic regions: metropolitan area (PALME 0), city (PALME 1), suburban (PALME 2), medium-sized town (PALME 3), intensive industrial region (PALME 4), intensive touristic region (PALME 5), extensive industrial region (PALME 6), touristic periphery (PALME 8),

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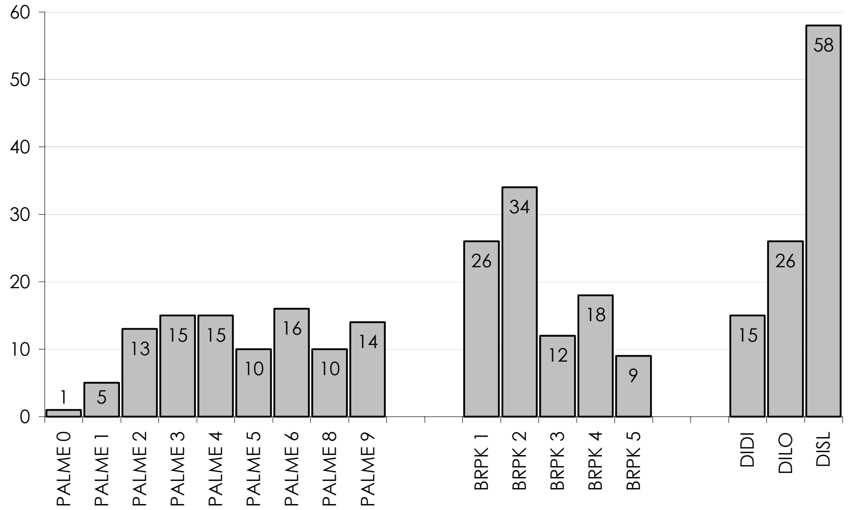
[5]) According to *Mayerhofer* (2002) the area of an Austrian administrative district is 847 square kilometers on average, and its population is roughly 87.000.

industrial periphery (PALME 9). The same line of reasoning as outlined above suggests that banks, for example, operating in a metropolitan area, city or suburban may be able to sustain a higher level of managerial (or internal) efficiency than banks doing business in rural or less developed regions such as touristic or industrial peripheries[6]).

3.1 Empirical Findings

According to our analytical approach, we start with calculating the efficiency scores without incorporating environmental factors for our sample of Austrian banks on the basis of an input-oriented, variable returns-to-scale SBM model[7]). The period of analysis ranges from 1996 to 2002. A summary of the efficiency results of the profit-oriented model is reported in Table 3 and reveals a rather high degree of inefficiency. The scores range from 0.262 (1996) to 0.224 (2002). The low levels of efficiency are not uncommon in bank efficiency studies which do not account for environmental factors.

Figure 1: Regional Classification Schemes
Number of Administrative Districts



In a second step we try to account for the very environmental factors which are closely related to the local market conditions of a typical universal bank. Referring to the chosen

[6]) For robustness tests, we apply a third classification scheme of districts building on population density. Accordingly, the Austrian administrative districts are divided into three groups: regions of dense population (DIDI), regions of medium population density (DILO), and regions of sparse population (DISL). A detailed description of this grouping scheme is given in the Data Appendix. The rationale of this classification is that, for bank management, higher levels of banking efficiency may be easier to sustain in densely populated areas than in sparsely populated districts. This is mainly due to the fact that banks in densely populated areas are more likely to operate closer to their optimal size than banks in sparsely populated regions. Estimation results of this model are not reported but made available on request.

[7]) The relative efficiency scores and the related input slacks were obtained from the DEA Solver Professional Program due to *Cooper – Seifried – Tone* (2000). The author is very grateful to Prof. Tone who made possible the usage of the SBM-module of DEA Solver Professional which greatly facilitated the compilation of the Bootstrap estimator.

regional groupings of the data sample we run Tobit-censored regressions with the slacks of the cost components 'employee expenses', 'non-interest expenses' and 'risk-weighted assets, as measured by Basel I', as the dependent variables.

Table 2: Slack Equations – Bootstrap Tobit-censored Regression Results for 1996 and 2002 with c=1,000 Samples
SBM Stage 1 Total Input Slacks

	1996						2002					
	Employee expenses		Non-interest expenses		Risk-weighted assets		Employee expenses		Non-interest expenses		Risk-weighted assets	
BRPK 1	0.650	***	0.402	***	31.323	***	1.156	***	0.595	***	37.731	***
	(0.126)		(0.068)		(7.776)		(0.190)		(0.179)		(4.998)	
BRPK 2	0.730	***	0.387	***	34.549	***	1.226	***	0.602	***	45.074	***
	(0.125)		(0.060)		(7.862)		(0.195)		(0.192)		(7.317)	
BRPK 3	0.992	***	0.462	***	62.511	***	1.420	***	0.707	***	79.739	***
	(0.178)		(0.077)		(11.220)		(0.267)		(0.229)		(13.116)	
BRPK 4	1.072	***	0.587	***	72.209	***	1.795	***	0.913	***	96.426	***
	(0.218)		(0.126)		(20.425)		(0.304)		(0.254)		(30.481)	
BRPK 5[1])	1.361	***	1.113	***	74.396	**	1.505	***	1.582	***	143.190	**
	(0.327)		(0.315)		(27.352)		(0.257)		(0.399)		(48.325)	
PALME 0[1])	1.263	***	1.111	***	70.484	**	1.446	***	1.978	***	143.962	**
	(0.307)		(0.295)		(31.605)		(0.289)		(0.457)		(51.027)	
PALME 1	2.399	***	1.120	***	173.749	***	3.661	***	2.066	***	334.736	**
	(0.518)		(0.268)		(48.021)		(0.727)		(0.640)		(126.404)	
PALME 2	0.698	***	0.353	***	30.263	***	1.215	***	0.675	***	41.196	***
	(0.124)		(0.059)		(7.690)		(0.183)		(0.157)		(5.246)	
PALME 3	1.081	***	0.578	***	66.228	***	2.273	***	1.122	***	122.103	***
	(0.219)		(0.108)		(17.035)		(0.463)		(0.359)		(34.474)	
PALME 4	0.775	***	0.415	***	39.940	***	1.447	***	0.724	***	62.084	***
	(0.135)		(0.062)		(9.258)		(0.267)		(0.192)		(9.161)	
PALME 5	0.583	***	0.358	***	33.866	***	0.945	***	0.538	***	44.310	***
	(0.119)		(0.045)		(5.851)		(0.167)		(0.142)		(6.218)	
PALME 6	0.645	***	0.389	***	28.822	***	1.103	***	0.591	***	38.983	***
	(0.125)		(0.060)		(7.557)		(0.185)		(0.155)		(5.840)	
PALME 8	0.573	***	0.328	***	25.492	***	0.816	***	0.442	***	26.289	***
	(0.113)		(0.056)		(6.794)		(0.147)		(0.116)		(4.295)	
PALME 9	0,600	***	0.333	***	24.027	***	1.121	***	0.578	***	36.469	***
	(0.107)		(0.057)		(6.506)		(0.186)		(0.146)		(6.116)	

***... significant at the 1% critical level, **... significant at the 5% critical level; standard errors in parentheses.
[1]) This variable includes or consists of the 23 boroughs of Vienna, respectively.

Since the results of the DEA-based Tobit regressions are biased due to the dependency problems we use the Bootstrap estimates with c=1,000 to adjust the inputs for the environmental bias. As illustration, in Table 2 we report the Bootstrap Tobit regressions results of the three slack equations based on the income per capita classification scheme and the regional classification proposed by *Palme* (1995), respectively, for the years 1996 and 2002. The findings corroborate the expectation that those banks which are located in a metropolitan area, city, or suburban region tend to maintain a higher level of technical efficiency than banks sitting in rural or peripheral regions. The same holds true when we use income per capita and population density as proxies for external factors determining local banking markets conditions. Banks in high-income or densely populated areas attain, on average, a significant higher level of technical or internal efficiency than banks working primarily markets in low-income or sparsely populated districts. It is worth mentioning that these results are robust over time, that is, we get similar results for each year, from 1996 to 2002.

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 according to the regional classification due to *Palme* (1995), income per capita, or population density elevates the average efficiency over the period of analysis significantly. The technical efficiency level of the entire Austrian banking sector in 2002 runs as high as 0.45 after controlling for the local banking markets conditions along the lines of the regional classification due to *Palme* (1995) compared to 0.22 based on the initial inputs. Importantly, the two efficiency estimates have little in common, they are only weakly correlated with each other (Table 3, last column). Again, this holds true regardless the year of investigation, from 1996 to 2002, or the proposed classification scheme of the 99 Austrian administrative districts.

Table 3: Austrian Banking Sector – Initial versus Adjusted Efficiency Scores

Regional Classification Scheme Due to Palme (1995)

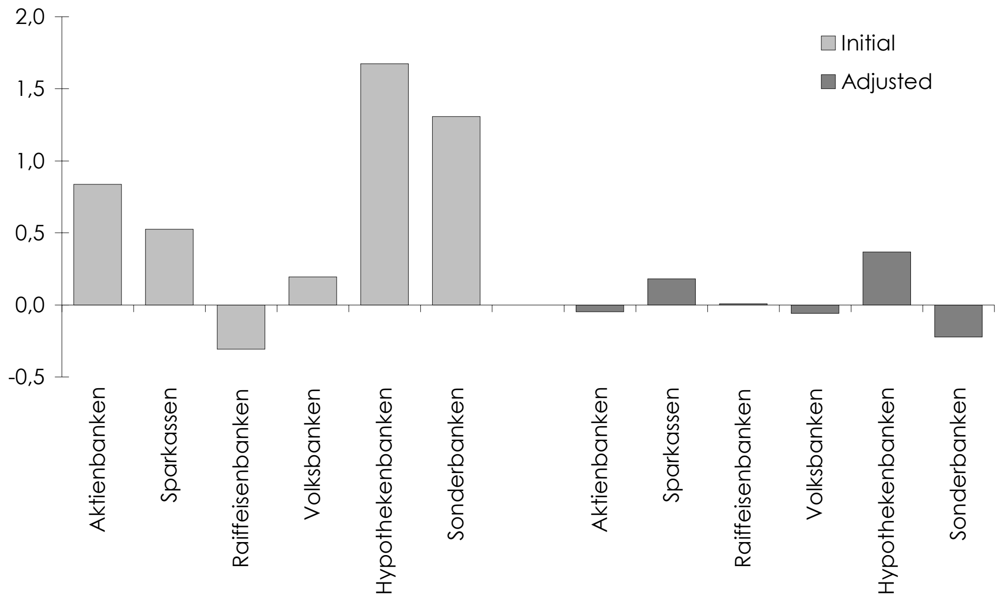
Average Scores of all Banks

		Initial efficiency scores			Adjusted efficiency scores			Correlation coefficient[1])
		Mean	Standard deviation	Coefficient of variation	Mean	Standard deviation	Coefficient of variation	
1996	Aktienbanken	0.457	0.346	0.757	0.440	0.321	0.730	0.829
	Sparkassen	0.411	0.224	0.545	0.639	0.155	0.243	0.597
	Raiffeisenbanken	0.186	0.106	0.570	0.540	0.134	0.248	0.207
	Volksbanken	0.315	0.182	0.578	0.476	0.183	0.384	–0.109
	Hypothekenbanken	0.742	0.281	0.379	0.733	0.251	0.342	0.992
	Sonderbanken	0.528	0.370	0.701	0.254	0.269	1.059	0.333
	All banks	0.262	0.220	0.840	0.517	0.193	0.373	0.192
2002	Aktienbanken	0.412	0.304	0.738	0.428	0.273	0.638	0.868
	Sparkassen	0.342	0.223	0.652	0.530	0.159	0.300	0.864
	Raiffeisenbanken	0.156	0.100	0.641	0.453	0.146	0.322	0.219
	Volksbanken	0.268	0.167	0.623	0.423	0.150	0.355	0.012
	Hypothekenbanken	0.600	0.251	0.418	0.614	0.224	0.365	0.995
	Sonderbanken	0.517	0.380	0.735	0.349	0.296	0.848	0.577
	All banks	0.224	0.207	0.924	0.449	0.177	0.394	0.347

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

Controlling for external local markets condition not only elevates the average banking efficiency score of the Austrian banking sector but also reduces the average range of volatility. As measured by the coefficient of variation, the spread of banking efficiency decreases, on average, respectively, by a margin of approximately 60 percent when, according to *Palme* (1995), local market conditions are controlled for (Table 3). Further, a decomposition of the initial and environment-adjusted efficiency scores along the lines of the traditional segmentation of the Austrian banking system yields that managerial efficiency of the commercial banks (Aktienbanken) tends to be overrated due to favorable environmental factors and that of cooperative banks (Raiffeisenbanken) to be underrated due to harsher local market conditions (Figure 2). Efficiency levels of savings banks (Sparkassen) and mortgage banks (Hypothekenbanken), however, remain unaffected by changing environmental factors.

Figure 2: Deviation from the Average Efficiency Score of all Banks 2002
Regional Classification Scheme due to Palme (1995)



4. Conclusion

In this paper we assess the technical efficiency (or X-efficiency) of the Austrian banking sector with the focus on environmental and non-controllable factors critical to banking markets. For this purpose we use a slacks-based DEA model (SBM) in combination with a Tobit regression approach to account for potential environmental and market influences on banking efficiency. In order to cope with the inherent dependency problem of DEA-based efficiency scores when incorporated into regression analysis we apply a Bootstrap estimator. In so doing we attempt to overcome the dependency problem which plagues the power of standard regression analysis based on DEA processed data.

The empirical analysis is based on an unbalanced panel of data covering more than 800 Austrian banks each year ranging over 1996 to 2002. The analysis shows, that controlling for the impact of environmental factors according to the various regional classification schemes significantly elevates the average efficiency over the period of investigation. Further, initial and environment-adjusted efficiency estimates have little in common, they are only weakly correlated with each other. Again, this holds true regardless of the year of investigation or the classification scheme of the 99 Austrian administrative districts.

Controlling for external local markets condition not only elevates the average banking efficiency score of the Austrian banking sector but also reduces the average range of volatility. As measured by the coefficient of variation, the spread of banking efficiency decreases, on average, respectively, by a margin of approximately 60 percent when local market conditions are appropriately controlled for. Finally, a decomposition of the initial and environment-adjusted efficiency scores along the lines of the traditional segmentation of the Austrian banking system yields that managerial efficiency of the commercial banks (Aktienbanken) tends to be overrated due to favorable environmental factors and that of cooperative banks (Raiffeisenbanken) to be underrated due to harsher local market conditions. Efficiency levels of savings banks (Sparkassen) and mortgage banks (Hypothekenbanken), however, remain unaffected by changing environmental conditions.

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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
BRPK j	Gross regional (NUTS 3) product per capita, divided by quintiles, j = 1, ..., 5	Statistics Austria
PALME 0	Metropolitan area	Palme (1995)
PALME 1	City	
PALME 2	Suburban	
PALME 3	Medium-sized town	
PALME 4	Intensive industrial region	
PALME 5	Intensive touristic region	
PALME 6	Extensive industrial region	
PALME 8	Touristic periphery	
PALME 9	Industrial periphery	
DIDI	Densely populated districts	Doubek – Winkler (1995), p. 18.
DILO	Medium populated districts	
DISL	Sparsely populated districts	

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