PRODUCTIVITY DRIVERS IN EUROPEAN BANKING: COUNTRY EFFECTS, LEGAL TRADITION AND MARKET DYNAMICS

Carlos Pestana Barros[1] ,Guglielmo Maria Caporale[2*]
and Margarida Abreu[1]

1 Instituto Superior de Economia e Gestão, Technical University of Lisbon
2 Centre for Empirical Finance, Brunel University, London

January 2008

Abstract

This paper analyses efficiency drivers of a representative sample of European banks by means of the two-stage procedure proposed by Simar and Wilson (2007). In the first stage, the technical efficiency of banks is estimated using DEA (data envelopment analysis) in order to establish which of them are most efficient. Their ranking is based on total productivity in the period 1993-2003. In the second stage, the Simar and Wilson (2007) procedure is used to bootstrap the DEA scores with a truncated bootstrapped regression. The policy implications of our findings are considered.

Keywords: European Banks; Data Envelopment Analysis; Truncated Bootstrapped Regression.

JEL Classification: G21, D24

*** Corresponding author.** Centre for Empirical Finance, Brunel University, Uxbrigde, Middlesex, UB8 3PH, UK. Tel. +44 (101895 266713. Email: Guglielmo-Maria.Caporale@brunel.ac.uk

1. Introdution

Efficiency analysis in European banking is a well-established line of research. Studies in this field include Molyneux et al. (1996), Altunbas et al. (2001), Goddard et al., (2001), Bikker and Haaf, (2002) and Maudos et al. (2002), Schure et al. (2004), Barros et al. (2007) and Williams et al. (2008). Factors such as legal tradition, accounting conventions, regulatory structures, property rights, culture and religion have been suggested as possible explanations for cross-border variations in financial development and economic growth (Beck et al., 2003a, b; Beck and Levine, 2004; La Porta et al., 1997, 1998; Levine, 2003, 2004; Levine et al., 2000; Stulz and Williamson, 2003). In addition, market dynamics have also been considered, as bank profits have been found to be procyclical (Arpa et al, 2001; Bikker and Hu, 2002), similarly to provisions for loan losses, which can exert a negative impact on the level of economic activity (see Cortavarria et al., 2000; Cavallo and Majnoni, 2002; Laeven and Majnoni, 2003). Another strand of literature emphasises the importance of market structure and bank-specific variables in explaining performance heterogeneities across banks. This strand developed around the structure-conduct-performance (SCP) paradigm and has been extended to contestable markets, firm-level efficiency and the roles of ownership and governance in explaining bank performance (see Berger, 1995; Berger and Humphrey, 1997; Bikker and Haaf, 2002; Goddard et al., 2001; Molyneux et al., 1996). In general, the extensive empirical evidence does not provide conclusive proof that bank performance is explained either by concentrated market structures and collusive price-setting behaviour or superior management and production techniques. Bank efficiency levels are found to vary widely across European banks and banking sectors (see Altunbaş et al., 2001; Maudos et al., 2002; Schure et al., 2004).

In this paper, the technical efficiency of a representative sample of European banks from 1993 to 2003 is analysed with a simultaneous two-stage procedure: in the first stage, Data Envelopment Analysis (DEA) is used to estimate the relative efficiency scores ranking banks according to their efficiency (Charnes, Cooper and Rhodes, 1978).[1] In the second stage, the Simar and Wilson (2007) procedure is applied to bootstrap the DEA scores with a truncated regression. Using this approach enables us to obtain more reliable evidence compared to previous studies analysing the efficiency of European banks, as the Simar and Wilson (2007) procedure ensures the efficient estimation of the second-stage estimators, which is not a property of alternative methods. First, the true efficiency score θ is not observed directly but is empirically estimated. Thus, the usual estimation procedures that assume independently-distributed error terms are not valid. Second, the empirical estimates of the efficiency frontier are obtained based on the chosen sample of banks, thereby ruling out some efficiency production possibilities not observed in the sample. This implies that the empirical estimates of efficiency are upwardly biased (Simar and Wilson, 2007). Thirdly, the two-stage procedure also depends upon other explanatory variables, which are not taken into account in the first-stage efficiency estimation. This implies that the error term must be correlated with the second-stage explanatory variables. Fourthly, the domain of the efficient score θ is restricted to the zero-one interval, which should be taken into account in the second-stage estimation (Simar and Wilson, 2007). The method introduced by Simar and Wilson (2007) overcomes these difficulties by adopting a procedure based on a double bootstrap that enables

[1] DEA was first introduced by Farrell (1957) and then developed by Charnes, Cooper and Rhodes (1978) as a non-parametric procedure that compares a decision unit with an efficient frontier, using performance indicators.

consistent inference within models, explaining efficiency scores while simultaneously producing standard errors and their confidence intervals. As shown by these authors, the alternative bootstrap procedure adopted by Xue and Harker (1999) is inconsistent. Moreover, the truncated bootstrapped second-stage regression proposed by Simar and Wilson (2007) accounts for the efficiency scores better than a Tobit model. .

The layout of the paper is the following. Section 2 briefly discusses the theoretical literature motivating our empirical analysis. Section 3 outlines the two-stage procedure of Simar and Wilson (2007). Section 4 presents the empirical results. Section 5 draws some policy implications and concludes.

2. Theoretical Framework

There are two main types of theoretical models providing an explanation for within-industry variation in efficiency. The first are based on strategic-group theory (Caves and Porter, 1977), which explains differences in efficiency scores as being due to differences in the structural characteristics of units within an industry, which in turn lead to differences in performance. In the case of European banking, units with similar asset configurations pursue similar strategies, with similar results in terms of performance (Porter, 1979). Although there are different strategic options in different sectors of an industry, owing to mobility impediments, not all options are available to each bank, causing a spread in the efficiency scores of the banking industry. The second type of model adopted is the resource-based one (Barney, 1991; Rumelt, 1991; Wernerfelt, 1984), which justifies different efficiency scores in terms of heterogeneity in resources and skills on which banks base their strategies. These may not be perfectly mobile across the industry, resulting in a competitive advantage for the best-performing banks. An example of a resource is cultural tradition.

Purchasable assets cannot be considered sources of sustainable profits. In this respect crucial resources are those not available in the market but rather built up and accumulated on the banks' premises, their non-imitability and non-substitutability being dependent on the specific traits of their accumulation process. The difference in resources thus results in barriers to imitation (Rumelt, 1991) and in the bank managers' inability to alter their accumulated stock of resources over time. Such unique assets account for inherently differentiated levels of efficiency, sustainable profits ultimately being a return on them (Teece et al., 1997).

3. Empirical Methodology

As mentioned above, we follow the two-stage approach of Simar and Wilson (2007). The DEA model used in the first stage of our empirical analysis is a non-parametric technique that allows the inclusion of multiple inputs and outputs in the production frontier. Following Farrell (1957), Charnes *et al*. (1978) first introduced the term "Data Envelopment Analysis" to describe a mathematical programming approach to estimating production frontiers and measuring efficiency relative to the frontier.

Estimation of Efficiency Scores

To estimate efficiency scores for each observation, we use a DEA estimator. The DEA approach usually (but not always) assumes that all banks, or more broadly, decision-making units (DMUs) within a sample have access to the same technology for transforming a vector of N inputs, denoted by x, into a vector of M outputs, denoted by y. We assume that technology can be characterised by the technology set, T, defined as:

$$T = \{(x, y) \in \Re_+^N \times \Re_+^M \quad : \quad x \in \Re_+^N \quad \textit{can produce} \quad y \in \Re_+^M\}. \tag{1}$$

Moreover, we assume that standard regularity conditions of the neo-classical production theory hold (for details, see Färe and Primont,, 1995). Having access to the same technology, any of the DMUs may or may not be on the frontier; the distance of a particular DMU from it may depend on various factors, specific to the DMU. These factors may be endogenous to the DMU, such as internal economic incentives influenced by the ownership structure, management quality, etc., and/or exogenous, such as different macroeconomic and demographic conditions, government regulation policies, etc. The distance from the actual location of each DMU given its technology set T from the frontier of T is thought to represent the inefficiency of each DMU, caused by the DMU's specific endogenous or exogenous factors and some unexplained statistical noise. Our goal is to measure such inefficiency and investigate its dependency on efficiency drivers.

In the first stage of our analysis we estimate efficiency scores for each DMU j ($j=1,\ldots,\ n$), using the Farrell/Debreu-type output-oriented technical efficiency measure:

$$TE(x^j, y^j) = \max_{\theta}\{\theta \quad : \quad (x^j, \theta\, y^j) \in T\}. \tag{2}$$

In practice, T is unobserved, thus we replace it with its DEA-estimate, $\hat{T}$:

$$\hat{T} = \{(x, y) \in \Re_+^N \times \Re_+^M \quad : \quad \sum_{k=1}^{n} z_k y_m^k \geq y_m, \quad m = 1, \ldots, M, \quad \sum_{k=1}^{n} z_k x_i^k \leq x_i\ ,$$
$$i = 1, \ldots, N,\ z_k \geq 0\ , \quad k = 1, \ldots\ ,\ n\ \}. \tag{3}$$

where $z_k \geq 0$ ($k = 1, \ldots, n$) are the intensity variables over which optimisation (2) is made. Geometrically, $\hat{T}$ is the smallest convex free-disposal cone (in the (x, y)-space) that contains (or 'envelopes') the input-output data. For more details on DEA, see Fare, Grosskopf and Lovel (1994), Charnes et al. (1995), Coelli, Prasada and Battese (1998), Copper et al. (2000) and Thanassoulis (2001), etc.

This is a consistent estimator of the unobserved true technology set *T*, under the assumption of constant returns to scale (CRS). Alternatively, non-increasing returns to scale (NIRS) or variable returns to scale (VRS) can be considered by adding to (3) the constraint $\sum_{k=1}^{n} z_k \leq 1$ or $\sum_{k=1}^{n} z_k = 1$, respectively. In this paper, we assume CRS to be able to discriminate better between DMUs and then analyse the returns-to-scale component in the second stage. The proof of consistency also requires certain regularity conditions (see Kneip et al., 1998, 2003, for these conditions, the resulting rates of convergence and the limiting distribution of the DEA estimator).

We choose this particular efficiency measure over others for several reasons. First, it satisfies a set of desirable mathematical properties. These properties include various forms of *continuity*, (weak) monotonicity, commensurability, homogeneity and (weak) indication for all technologies satisfying certain regularity conditions (see Russell (1990, 1997, for details). Secondly, this measure is also relatively easy to compute and straightforward to interpret, and therefore the most widely adopted in practice.

The estimates of the efficiency scores, $\hat{TE}_j$ ($j=1,\ldots,n$), obtained by replacing T with $\hat{T}$ in (2) are consistent estimates of the corresponding true efficiency scores, TE_j ($j=1,\ldots,n$) given by (2). They are bounded between unity and infinity, with unity representing an estimated perfect (technical or technological) efficiency score of 100%. On the other hand, $(1/\hat{TE}_j)$ would represent the estimated relative *%-level* of the efficiency of the j^{th} DMU ($j= 1,\ldots, n$), relative to the estimated best-practice technology frontier, $\hat{T}$.

Regression Analysis of Determinants of Efficiency

Next, following Simar and Wilson (2007), we briefly outline regression analysis for studying dependency between the efficiency scores and hypothesised explanatory variables. We assume and test the following specification:

$$TE_j = a + Z_j\delta + \varepsilon_j, \qquad j = 1, \ldots, n \tag{4}$$

which can be interpreted as the first-order approximation of the unknown true relationship. In equation (4), a is the constant term, ε_j is statistical noise, and Z_j is a (row) vector of observation-specific variables for DMU_j that we expect to affect its efficiency score, TE_j, through the vector of parameters δ (common for all j) that we need to estimate.

A common practice in the DEA literature for estimating model (4) had previously been to employ the Tobit-estimator, until Simar and Wilson (2007) highlighted the limitations of such an approach. Instead, they introduced a method based on a truncated regression with a bootstrap and illustrated through Montecarlo experiments its satisfactory performance. Here, we will employ their approach. Specifically, noting that the distribution of ε_j is restricted by the condition $\varepsilon_j \geq 1 - a - Z_j\delta$ (since both sides of (7) are bounded by unity), we follow Simar and Wilson (2007) and assume that this distribution is truncated normal with zero mean (before truncation), unknown variance and a (left) truncation point determined by this very condition. Furthermore, we replace the true but unobserved regressand in (4), TE_j, by its DEA estimate $T\hat{E}_j$. Formally, our econometric model is given by:

$$T\hat{E}_j \approx a + Z_j\delta + \varepsilon_j, \qquad j = 1, \ldots, n, \tag{5}$$

where

$$\varepsilon_j \sim N(0, \sigma_\varepsilon^2), \text{ such that } \quad \varepsilon_j \geq 1 - a - Z_j\delta, \quad j = 1, \ldots, n, \tag{6}$$

which we estimate by maximising the corresponding likelihood function, with respect to $(\delta, \sigma_\varepsilon^2)$, given our data. Relying on asymptotic theory, normal tables can be used to construct confidence intervals but more precision can be gained by using the bootstrap. This is particularly so because in our analysis the regressand is not an observed variable, but an estimate that is likely to be dependent on unobserved variables (see Simar and Wilson, 2007, for details). To construct the bootstrap confidence intervals for the estimates of the parameters $(\delta, \sigma_\varepsilon^2)$, we use a parametric bootstrap regression method, which incorporates information on the parametric structure and distributional assumption. Details of the estimation algorithm can be found in Simar and Wilson (2007).

4. Empirical Analysis

Data Description and Sources

Financial statement data for commercial banks operating in thirteen EU countries between 1993 and 2003 were obtained from the BankScope database. The sample chosen requires an explanation. We evaluate domestic and foreign bank performance; the latter are bank subsidiaries rather than branches.[2] Prior to the creation of the internal market in 1993, numerous foreign branches were converted into subsidiary operations to take advantage of new EC directives and enable competition with domestic banks (European Comission, 1997). From 1993 to 2001, banks were exposed to European currency risks, which were eliminated for EU-owned banks upon the introduction of the Euro. However, other foreign banks have remained subject to currency risk, which could cause biased estimates of bank performance. These reasons explain the cut-off points used in this study, (ECB, 2004). Two main approaches are adopted in banking to model the frontier, the production approach and the intermediate approach (Sealey and Lindley, 1977). In this paper the intermediate approach is adopted.

Table 1: Descriptive Statistics: Euro million (inflation-adjusted); 1993-2003

		Inputs		*Outputs*			
Country	*Statistic*	*Fixed Assets*	*Variable Cost*	*Customer Loans*	*Interbank Loans*	*Securities*	*Off-balance-sheet*
Austria	Average	48.4	263.4	2,801.5	1,474.1	975.0	224.7
	Std dev	224.7	1,023.6	11,275.4	5,589.0	4,171.7	1,028.7

[2] Foreign-owned banks are classified as banks with 50% or more foreign holdings.

Belgium	Average	263.8	1,409.8	11,154.5	5,778.7	8,771.2	46,139.8
	Std dev	46,139.8	3,492.8	29,153.9	14,780.5	21,893.3	282,722.8
Finland	Average	401.3	1,449.1	18,860.6	4,614.4	5,350.4	6,496.0
	Std dev	6,496.0	2,300.9	32,981.1	6,944.4	7,424.8	10,869.9
France	Average	132.9	1,064.0	6,572.4	3,745.3	4,945.4	4,781.0
	Std dev	608.2	3,959.3	25,007.7	15,361.6	22,200.5	20,896.1
Germany	Average	105.7	724.4	6,598.4	2,153.9	3,570.8	2,312.8
	Std dev	671.2	4,271.4	35,479.6	10,509.2	25,861.5	13,455.1
Greece	Average	211.7	768.8	4,744.8	1,717.7	3,186.4	10,748.8
	Std dev	276.1	1,093.0	6,008.3	2,847.7	5,312.5	17,235.3
Ireland	Average	110.9	646.1	6,494.1	1,716.6	3,410.0	427.7
	Std dev	298.3	1,268.8	14,221.9	2,543.6	8,722.9	1,079.9
Italy	Average	263.2	954.1	8,886.2	2,649.4	2,609.8	4,559.9
	Std dev	717.6	2,625.6	25,336.7	7,497.5	7,720.2	16,170.0
Luxembourg	Average	18.5	333.6	1,061.0	2,285.5	1,271.7	602.9
	Std dev	57.6	679.4	2,455.8	4,242.1	2,777.2	1,631.9
Netherlands	Average	427.8	2,225.9	21,960.8	4,244.4	8,303.7	7,644.1
	Std dev	1,416.0	6,963.0	64,555.1	13,199.3	29,416.4	30,076.8
Portugal	Average	163.8	582.7	5,412.4	1,727.1	1,422.8	3,352.5
	Std dev	271.2	855.9	9,530.9	2,349.8	2,139.4	5,919.6
Spain	Average	291.7	915.4	7,125.7	1,496.0	3,627.6	1,080.2
	Std dev	1,076.9	3,689.9	25,144.5	5,040.5	15,462.0	3,852.8
UK	Average	581.2	1010.2	8,527.3	2,532.3	5,219.2	4,321.5
	Std dev	1,210.4	2125.3	12,318.4	2,219.5	21,219.3	12,219.3

DEA Results

The DEA index can be calculated in several ways. Here, we estimate an output-oriented, technically efficient (TE) DEA index, assuming that banks aim to maximise the profits resulting from their activity. In this context, inputs are exogenous and outputs endogenous because of the competitive environment in which the units operate (Kumbhakar, 1987).

CCR efficient score model, is probably the most widely used and best known DEA model. It is the DEA model that assumes constant returns to scale relationship between inputs and outputs. It is named following their authors, Charnes, Cooper and Rhodes (1978) and measures the overall efficiency for each unit, namely aggregating pure technical efficiency and scale efficiency into one value, Gollani and Roll (1989).

The BCC efficient score model is a DEA model that assumes variable returns to scale between inputs and outputs. It is named following their authors, Banker, Charnes and Cooper (1984) and measure pure technical efficiency alone, Gollani and Roll (1989). The efficiency score obtained with the BCC model gives a score which is at least equal to the score obtained using the CCR. The scale efficiency score is obtained dividing the aggregate CCR score by the technical efficient BCC score, (Fare et al, 1994). A unit is scale efficient when its size of operation is optimal. If its size is either reduced or increased its efficiency will drop. Assuming that pure technical efficiency is attributed to managerial skills, the BCC scores are interpreted as managerial skills. All the DEA scores used in the paper are called ratio models, because they define efficiency as the ratio of weighted outputs divided by the weighted inputs. They use a radial or proportionate measure to determine the technical efficiency. A unit's technical efficiency is defined by the ratio of the distance from the origin to the inefficient unit, divided by the distance from the origin to the composite unit on the efficient frontier.

Variable returns-to-scale (VRS) were assumed to decompose technical efficiency into two different components: pure technical efficiency and scale efficiency (Fare et al, 1994). The VRS scores measure pure technical efficiency. However, the constant returns-to-scale (CRS) index is composed of a non-additive combination of pure technical and scale efficiencies. A ratio of overall efficiency scores to pure technical efficiency scores provides a measurement of scale efficiency.

The relative efficiency of European banks is presented in Table 2, with the banks aggregated by country, using a MATLAB program.

Table 2: Efficiency in European Banks

Country	DEA-CCR model	DEA-BCC Model	Scale Efficiency
Austria	0.951	0.958	0.993
Belgium	0.950	0.954	0.996
Finland	1.000	1.000	1.000
France	0.981	1.000	0.981
Germany	0.973	1.000	0.973
Greece	0.958	0.972	0.986
Ireland	0.954	0.971	0.982
Italy	0.983	1.000	0.983
Luxembourg	0.952	0.965	0.987
Netherlands	0.971	0.981	0.990
Portugal	0.975	0.982	0.993
Spain	0.985	1.000	0.985
UK	1.000	1.000	1.000
Mean	0.969	0.982	0.987
Median	0.972	0.982	0.986
St.Dev.	0.016	0.018	0.007

A number of points emerge. Firstly, consistently with previous research on European banking, there appear to be significant differences in efficiency among the banks analysed (Berger, 1995; Berger and Humphrey, 1997; Bikker and Haaf, 2002;

Goddard et al., 2001; Molyneux et al., 1996). Note that the DEA score is between zero (0%) and 1 (100%). Units with DEA scores equal to 1 (100%) are efficient. A unit with a score of less than 100% is relatively inefficient, e.g. a unit with a score of 95% is only 95% as efficient as the best-performing banks. Scores are relative to the other units, i.e., they are not absolute. Secondly, best-practice calculations indicate that almost all European banks operated at a high level of pure technical efficiency in the period under examination.

Finally, all technically efficient CRS banks are also technically efficient in VRS, indicating that the dominant source of efficiency is scale (Gollani and Roll, 1989). CRS is assumed if an increase in a unit's input leads to a proportionate increase in its outputs. This means that, regardless of the scale at which the unit operates, its efficiency will remain unchanged, assuming its current operating practices. VRS can be either increasing or decreasing returns to scale. In the former case an increase in a unit's inputs yields a greater than proportionate increase in its outputs; in the latter, a decrease in a unit's inputs yields a lower than proportionate increase in output. The above evidence suggests that variable returns to scale better characterise the technical efficiency of European banks.

Determinants of Efficiency

In order to examine the hypothesis that the efficiency of the European banks is determined by different variables, we followed the two-step approach, as suggested by Coelli *et al*. (1998), estimating the regression shown below. It is recognised in the DEA literature that the efficiency scores obtained in the first stage are correlated with the explanatory variables used in the second stage, and that the second-stage estimates will then be inconsistent and biased. A bootstrap procedure is needed to overcome this problem (Efron and Tibshirani, 1993). To this end, as explained earlier, we adopt the approach of Simar and Wilson (2007).

The estimated specification is as follows, Berger and Mester (1997):

$$\theta_{i,t} = \beta_0 + \beta_1.Trend_{i,t} + \beta_2.Trend_{i,t}^2 + \beta_3.Country_{i,t} + \beta_4 LegalTradition_{i,t} + \beta_5 X_{i,t} + \varepsilon_{i,t} \quad (7)$$

where θ represents the DEA-CCR model efficiency score, estimated in table 2. *Trend* is a yearly trend. *Square trend* is the square value of the trend. *Country* is a dummy variable, which is one for a specific European country and zero otherwise; this aims to capture the efficiency related to each European country. *Legal tradition* is a dummy variable which is one for countries with a specific legal tradition (English Common law, French Civil Code, Germanic tradition, Scandinavian tradition); this aims to capture efficiency orientation strategies inherent to each legal tradition. Finally, *X* is a continuous variable capturing bank characteristics (assets, loans, deposits). Following Simar and Wilson (2007), we employ a MATLAB program to bootstrap the confidence intervals, with 2000 replications. The results are presented in Table 3.

Table 3: Truncated Bootstrapped Second-Stage Regression (*dependent variable: CCR index)*

Variable	Model 1	Model 2	Model 3
Constant	1.16***	1.10***	1.16***
Trend	0.11***	0.09**	0.19***
Square trend	-0.03***	-0.07**	-0.07**
Country			

Austria	0.035**	0.0044**	0.041**
Belgium	0.03**	0.00**	0.04**
Finland	0.16***	0.13***	0.15***
France	0.01***	0.012***	0.02***
Germany	0.06***	0.07***	0.06***
Greece	0.02**	0.04***	0.04***
Ireland	0.03**	0.03**	0.04**
Italy	1.16***	1.10***	1.16***
Luxembourg	0.11***	0.09**	0.19***
Netherlands	0.03**	0.07**	0.07**
Portugal	0.03**	0.03**	0.04**
Spain	0.05**	0.07**	0.08**
UK	0.12*	0.10*	0.09*
Legal Tradition			
English Common law	0.07***	0.06***	0.05***
French Civil Code	0.05***	0.04***	0.03***
Germanic tradition	0.08***	0.07***	0.05***
Scandinavian tradition	0.05*	0.04	—
Banks' characteristics			
Foreign ownership	0.07***	0.05***	0.04***
Deposits market share[1]	0.23***	0.24***	0.25***
Loans market share[1]	0.08***	0.07**	0.05**
Assets market share[1]	0.02	—	—
Variance	0.03	0.03	0.04

(1) The percentage of assets, loans and customer deposits held by the bank to the total amount of each variable over the period.

***, **, * statistically significant at 1%, 5%, and 10% respectively.

Several models were estimated for comparison purposes. The results are quite robust, since the variables that were significant in Model 1 remained significant after dropping the insignificant variables. Also, country variables all have a positive and statistically significant coefficient. Legal tradition also has positive and significant effect in all models, with the exception of Scandinavian tradition, which is insignificant in Model 2. Finally, deposits' and loans' market share both have positive and significant coefficients, while assets' market share is statistically insignificant.

5. Conclusions

In this paper we have adopted the DEA two-stage model to analyse the performance of domestic and foreign commercial banks operating in the EU between 1993 and 2003. The main innovation in our analysis is to apply the two-stage procedure proposed by Simar and Wilson (2007) to bootstrap the DEA scores. This procedure improves both efficiency of estimation and inference. In particular, the adoption of the functional form (truncated functional form) in the second stage enables consistent inference with models explaining efficiency scores, while simultaneously producing standard errors and confidence intervals for these efficiency scores. Benchmarks can be obtained for improving the operations of banks that perform poorly.

Our empirical findings suggest the following: First, legal tradition and foreign ownership have implications for public policy. EU policymakers use deregulation to increase competition in the banking sector and the wider financial system: initiatives like the Financial Services Action Plan have encouraged a competitive and market-based structure in the financial services industry, Claessens et al. (2001). Our results imply that competition can be enhanced by policies designed to increase foreign bank penetration, Barros et al. (2007). The evidence supports the argument that competitive, well-regulated markets and the promotion of private property rights and contractual rights help banks to gain efficiency advantages that can be exported successfully Humphrey and Pulley, (1997). Therefore, EU policymakers should continue to implement policies that increase competition and legislate against any remaining legal and regulatory obstacles to competition. The projected expansion of US banks within the Euro Area can be expected to have a similar effect on competition and should also be encouraged, Berger et al. (2000).

It also seems that location does not affect performance significantly. This is instead explained by bank size and the relative importance of banks' traditional activities. Banks with a relatively larger share of the total deposits collected are more likely to perform better, as are banks with a higher percentage of loans. Moreover, the larger the relative size of a bank, the more likely it is to perform well. This result supports the conclusion of most empirical studies in banking regarding the existence of slight economies of scale in the banking industry, and also justifies the European authorities' efforts to reinforce the bank consolidation process initiated in the early 1990s, Williams et al. (2007). More research is needed to confirm the present results.

.

REFERENCES

Altunbaş, Y., Gardener, E.P.M., Molyneux, P., Moore, B., 2001. Efficiency in European banking. European Economic Review 45, 1931-1955.

Arpa, M., Giulini, I., Ittner, A., Pauer, F., 2001. The influence of macroeoconomic developments on Austrian banks: implications for banking supervision. BIS Papers, 1, 91-116.

Barney J. (1991). Firm resources and sustained competitive advantage. *Journal of Management,* Vol. 17, pp. 99-120.

Banker, R.D., Charnes, A., Cooper, W. W., 1984. Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. Management Science 30, 1078-1092.

Barros, C.P.; Ferreira, C. and Williams, J. (2007) Analysing the Determinants of Performance of the Best and Worst European banks: A Mixed Logit Approach. Journal of Banking and Finance, 31, 2189-2203.

Beck, T., Demirgüç-Kunt, A., Levine, R., 2003a. Law, endowments, and finance. Journal of Financial Economics 70, 137–181.

Beck, T., Demirgüç-Kunt, A., Levine, R., 2003b. Law and finance. Why does legal origin matter? Journal of Comparative Economics 31, 653–675.

Beck. T., Levine, R., 2004. Stock Markets, Banks and Growth: Panel Evidence. Journal of Banking and Finance 28, 423-442.

Berger, A.N., 1995. The profit-structure relationship in banking: tests of market-power and efficient-structure hypotheses. Journal of Money, Credit and Banking 27, 2, 404-431.

Berger, A.N., Humphrey, D.B., 1997. Efficiency of financial institutions: International survey and directions for future research. European Journal of Operations Research 98, 175-212.

Berger, A.N., Mester, L.J., 1997. Inside the black box: What explains differences in the efficiencies of financial institutions? Journal of Banking and Finance 21, 895-947.

Berger, A.N., DeYoung, R., Genay, H., Udell, G.F., 2000. Globalisation of Financial Institutions: Evidence from Cross-Border Banking Performance, Brookings-Wharton Papers on Financial Services 3, 23-158.

Bikker, J.A., Hu, H., 2002. Cyclical patterns in profits, provisioning and lending of the new Basel capital requirements. DNB Staff Reports No.86.

Bikker, J.A., Haaf, K., 2002. Competition, concentration and their relationship: An empirical analysis of the banking industry. Journal of Banking and Finance 26, 2191-2214.

Caves R. and Porter M.E. (1977). From entry barriers to mobility barriers: Conjectural decisions and contrived deterrence to new competition, *Quarterly Journal of Economics*, Vol. 91, pp. 241-261.

Cavallo, M., Majnoni, G., 2002. Do Banks Provision for Bad Loans in Good Times? Empirical Evidence and Policy Implications. World Bank Policy Research Working Paper, No. 2619.

Charnes, A.; Cooper, W.W. and Rhodes, E., 1978, Measuring the Efficiency of Decision-Making Units, *European Journal of Operations Research*, 2, pp. 429-444.

Charnes, A.; Cooper, W.W., Lewin, A.Y. and Seiford, L.M., 1995, *Data Envelopment Analysis: Theory, Methodology and Applications*, Boston, Kluwer.

Claessens, S., Demirgüç-Kunt, A., Huizinga, H., 2001. How does foreign entry affect domestic banking markets? Journal of Banking and Finance 25, 891-911.

Coelli, T.J., Rao, P. and Battese, G.E., 1998, *An Introduction to Efficiency and Productivity Analysis*. Kluwer Academic Press.

Cortavarria, L., Dziobek, C., Kanaya, A., Song, I., 2000. Loan review, provisioning and macroeconomic linkages. IMF Working Paper, No. 00/195.

Cooper, W.W.; Seiford, L.M. and Tone, K., 2000, *Data Envelopment Analysis*. Boston, Kluwer.

ECB, 2004. Report on EU Banking Structure, November.

European Commission. 1997. *The Single Market Review, Subseries II: Impact on Services, Volume 3: Credit Institutions and Banking*, Kogan Page, Earthscan, London.

Efron, B., Tisbhirani, R.J., 1993. An introduction to the bootstrap, Chapman & Hall Ed.

Fare, R. S., Primont, D., 1995. Multi-output production and duality: Theory and applications, Kluwer Academic Publishers, Boston.

Fare, R. Grosskopf, S., S. , Lovell, C. A. K. , 1994. Production Frontiers. Cambridge University Press.

Farrell, M. J.,1957. The Measurement of Productive Efficiency. Journal of the Royal Statistical Society, Series A, 120, 253-290.

Goddard, J.A., Molyneux, P., Wilson, J.O.S., 2001. European Banking: Efficiency, Technology and Growth. (Chichester, UK: John Wiley & Sons).

Humphrey, D.B., Pulley, L.B., 1997. Banks' responses to deregulation: profits, technology, and efficiency. Journal of Money, Credit and Banking 29, 73-93.

Khumabhakar, S.C. (1987) Production frontiers and panel data: an application to US class 1 railroads, *Journal of Business and Economic Statistics*, 5 (2), pp. 249-255.

Kneip, A., Park, B., Simar, L., 1998. A note on the convergence of nonparametric DEA estimators for production efficiency scores. Economic Theory, 14, 783-793.

Kneip, A., Simar, L., Wilson, P.W., 2003. Asympotics for DEA estimation in non-parametric frontier models. Discussion paper of the Institut de Statistique, Université Catolique de Louvain, Belgium.

Laeven, L., Majnoni, G., 2003. Loan Loss provisioning and economic slowdowns: too much too late? Journal of Financial Intermediation 12, 178-97.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., Vishny, R., 1997. Legal Determinants of External Finance. Journal of Finance 52, 1131-1150.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., Vishny, R., 1998. Law and finance. Journal of Political Economy 106, 1113-1155.

Levine, R., 2003. Bank-based or market-based financial systems: which is better? Journal of Financial Intermediation 11, 398-428.

Levine, R., 2004. Finance and growth: Theory and evidence. NBER Working Paper No. 10766.

Levine, R., Loayza, N., Beck, T., 2000. Financial intermediation and growth: causality and causes. Journal of Monetary Economics 46, 31-77.

Maudos, J., Pastor, J.M., Pérez, F., Quesada, J., 2002. Cost and profit efficiency in European banks. Journal of International Financial Markets, Institutions and Money 12, 33-58.

Molyneux, P., Altunbaş, A., Gardener, E.P.M., 1996. Efficiency in European Banking. (Chichester, UK: John Wiley and Sons).

Porter, M.E. (1979). The structure within industries and companies' performance. *The Review of Economics and Statistics,* Vol. 61, pp. 214-227.

Rumelt, R., (1991). How much does industry matter? Strategic Management Journal 12 (2), 167-185.

Russell, R.R., 1990. Continuity of measures of technical efficiency. Journal of Economic Theory., 51, 255-267.

Russell, R.R.. 1997. Distance functions in consumer and producer theory. In: Index Number Theory: Essays in Honor of Sten Malmquist. Kluwer Academic Publishers, Boston , pp.7-90.

Sealey, C., Lindley, J.T., 1977. Inputs, outputs and a theory of production and cost at depository financial institution. Journal of Finance 32, 1251-1266.

Schure, P., Wagenvoort, R., O'Brien, D., 2004. The efficiency and the conduct of European banks: Developments after 1992. Review of Financial Economics 13, 371-396.

Simar, L. and P.W. Wilson (2007), "Estimation and inference in two-stage, semi-parametric models of productions processes", Journal of Econometrics, 136, 31-64.

Stulz, R. Williamson, R., 2003. Culture, openness, and finance. Journal of Financial Economics 70, 313–349.

Teece D.; Pisano G. and Shuen A. (1997), Dynamic capabilities and strategic management, *Strategic Management Journal,* Vol. 18, No. 7, 509-533.

Thanassoulis, E., 2001, *Introduction to the Theory and Application of Data Envelopment Analysis: A Foundation Text with Integrated Software*. Dordrecht, Kluwer Academic Publishers.

Xue, M., Harker, P.T., 1999. Extensions of Modified DEA. Financial Institution Center, Working Paper 99-07. The Wharton School, University of Pennsylvania.

Wernerfelt, B. (1984). "A resource-based view of the firm", *Strategic Management Journal,* Vol. 5, No. 2, 171-180.

Williams, J.; Peypoch, N. and Barros, C.P. (2007**).** The Luenberger indicator and productivity growth: A note on the European savings banks sector. Mimeo

Zhu, J., 2002. Quantitative Models for Performance Evaluation and Benchmarking: Data Envelopment Analysis with Spreadsheets, Kluwer Academic Publishers, Boston.