EFFICIENCY OF EUROPEAN BANKING SYSTEMS: A CORRECTION BY ENVIRONMENT VARIABLES*

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A B S T R A C T

In this paper we extend the efficiency cross-country comparisons to ten European countries in order to know how different or similar current banking performances are. We start with two types of comparisons. First of all, we evaluate the average technical efficiency of each country by means of a DEA model called "basic" model. This model includes only banking variables. Our second model, called "complete", does consider environmental variables together with the banking variables of the basic model. The empirical results recommended us to substitute the original environmental variables with new codified variables. Finally, the non homogeneity of the country-samples, observed after performing an individual DEA analysis for each country, was decisive for considering two new models, based on a modified sample. The comparisons between the last two models show that the country specific environmental conditions exercise a strong influence over the average efficiency score of each country.

JEL: D2, G21, O3

Key words: Efficiency, DEA, Environmental conditions, European banking.

R E S U M E N

El objetivo de este trabajo es comparar la eficiencia de diez países europeos. Para ello, el trabajo comienza con dos tipos de modelos. El primero analiza la eficiencia técnica media de cada país por medio de un modelo DEA que denominamos "modelo básico" y que incluye sólo variables bancarias. El segundo, llamado "modelo completo" incluye variables ambientales junto con las variables bancarias del modelo básico. Los resultados obtenidos en este segundo modelo recomendaron sustituir las variables ambientales originales por unas nuevas variables codificadas. Finalmente, la heterogeneidad de las muestras por países, observada después de realizar un análisis individual por país, lleva a considerar dos nuevos modelos, basados ambos en el modelo codificado. Las comparaciones entre estos dos modelos muestran que las condiciones ambientales de cada país ejercen una influencia muy fuerte en la eficiencia media de cada país.

JEL: D2, G21, O3

Palabras clave: Eficiencia, DEA, Condiciones ambientales, Banca Europea.

1. INTRODUCTION

In anticipation of the expected lowering of barriers to competition among financial institutions within the European Monetary Union (EMU), changes in regulation of financial markets have been adopted by many members of the EMU in the last years. Those changes were designed to liberalize the provision of services and to increase competition. This way, the banks will better adjust to the needs of the customers when they set up branches in any other country --subject only to the regulations of their home country--. As domestic markets become more competitive, current differences in performance among the banking industries of the EMU members will largely determine each country's banking structure and future competitive viability. Therefore, a matter of particular importance in the increasingly harmonized European market for banking services is to know, as best as possible, how different or similar are current banking performance between countries in order to better predict and/or prepare for expected increase in cross-border competition.

The international comparison analysis in banking efficiency scores has been investigated earlier, although it appears that the literature has paid little attention to this issue. Berg, Førsund, Hjalmarson, and Suominen, (1993, hear after BFHS), used DEA analysis in order to capture the differences in banking efficiency among Norway, Sweden, and Finland. Berg, Bukh, and Førsund, (1995, here after BBF) followed up the study by adding Denmark to the previous sample. The same four countries were investigated in Bergendahl, (1995) using mixed optimal strategy. Fecher, and Pestieau, (1993) and, Pastor, Pérez, and Quesada (1997) applied distribution free approach (DFA) and DEA analysis to 11 OECD countries and 8 developed countries, respectively. The former study found opposite results to those obtained by DFHS and BBF with regard to the efficiency levels of the same set of countries[1]. Allen and Rai (1996) used DFA and stochastic frontier approach (SFA) in order to carry out a systematic comparison of efficiency measures across 15 developed countries under different regulatory environments.

At the end, all these cross-country studies build a common frontier pooling the cross-country banks and assume that the banking efficiency differences between countries are only due to some country-specific aspects of the banking technology. In other words, they build the common frontier under the belief that the differences in efficiency across countries are only attributable to bank managerial decisions. However, it could be possible that the underlying

[1] See Berger and Humphrey (1997) for more details about the methodologies used and results obtained on those studies.

banking technology across European countries would be quite similar, being the differences in efficiency among countries largely determined by country-specific differences -that are almost always excluded from performance analysis-, and not only by technology differences. If the country-specific variables are an important factor in the explanation of the banking efficiency differences, then the common frontier obtained neglecting this factor will generate overestimated inefficiency levels[2].

With the aim of addressing the deficiencies found in the methodology used in the intercountry banking efficiency comparison studies, we propose in this study a new method based on DEA models. This is the first paper to undertake a systematic comparison of efficiency measures across countries taking into account environmental variables and using a non-parametric approach. Recently, Dietsch and Lozano (1996) undertook the same issue evaluating the cost efficiency of the French and Spanish banks, but using a parametric approach, DFA.

In what follows, the DEA models for evaluating the cross-country technical efficiency when the particular environmental conditions of each country are taken into account, as well as the procedure to detect the influence of environmental variables in a DEA framework is briefly introduced in Section 2. The description of the data and the specification of inputs, outputs and environmental variables are described in Section 3. Section 4 presents the empirical results based on the six considered DEA models, and, finally, we provide some concluding remarks in Section 5.

2. METHODOLOGY

The first exercise we propose is to evaluate the technical efficiency of the banking industry of different countries by means of a DEA model. Initially, we will consider "n" basic banking inputs and "m" basic banking outputs for each bank and resort to a BCC input-oriented model (Banker et al. (1984)). The mathematical formulation of this model is

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[2] Although the Allen and Rai´s paper takes into account the regulatory environments of each country in their intercountry banking efficiency comparison, those environmental variables are specified at the bank level and not at the country level. Moreover, these authors explain the differences in efficiency by doing an ex-post analysis.

$$
\text{Min } \boldsymbol{\theta} \text{ subject to} \qquad
\begin{aligned}
Y\boldsymbol{\tau} &\geq Y_0 \\
X\boldsymbol{\tau} &\geq X_0 \\
e^T\boldsymbol{\tau} &= 1 \\
\boldsymbol{\tau} &\geq 0_n ,
\end{aligned}
$$

where Y is the matrix of output-vectors; X is the matrix of input-vectors; (X_0,Y_0) is the unit being rated; e^T denotes a row-vector of 1´s; $\boldsymbol{\tau}$ is the vector of intensity variables; and $\boldsymbol{\theta}$ is the so called efficiency score --a quantity between 0 and 1--. If $\boldsymbol{\theta}$ is lower than 1, a proportional reduction of all inputs is needed in order to reach the efficient frontier. This reduction is exactly given by $(1-\boldsymbol{\theta})$ X_0, which means that the projected unit given by $(\boldsymbol{\theta}X_0, Y_0)$ is efficient in the sense of Debreu-Farrell or DEA weakly-efficient. No further radial reduction of all inputs is possible given the present amount of outputs. It could be that, in order to be Koopmans or DEA efficient some further individual reduction in some inputs and/or augmentation in some outputs is needed. For evaluating these mix-inefficiencies we need to resort to a more complex BCC model, --considering a non-Archimedean element in the objective function multiplied by the sum of the slack variables--. However, if the slacks are not important then we do not need to go further along this line[3]. The model considered in this first exercise is called "basic model".

The second exercise we propose is to run again the same evaluation but including this time the environmental variables into our DEA model. We claim that the banks of the countries with bad environmental conditions get overestimated values for their inefficiencies because they are not compared on an equal footing in relation to the banks from countries with good environmental conditions. There are several ways of evaluating the influence of environmental variables in a DEA framework (see Rouse (1996)). We propose here the easiest way of considering environmental factors in DEA: to incorporate them directly into the basic model. This approach has an initial restriction since we must know in advance the orientation of the influence of each environmental variable. In other words, each uncontrolled factor must have a known oriented influence.

In order to consider the environmental variables as inputs or outputs of our model we just reverse their condition: for example, if a given environmental variable is an input-type variable ("less means better") we consider it as an output in our model (see Cooper and Pastor (1996)).

[3] This is exactly what happens with the data in this paper, being always the amount of any slack value less than 5% of the corresponding variable value.

Moreover, all the environmental variables are treated as non-discretionary variables, in the classical sense[4]. This will be explained later on.

We consider a second DEA model, which is not the extension of the "m+n" variable basic model with all the "q" environmental factors but the extension of the "m+n" variable basic model with those environmental variables which change significantly the efficiency scores of the basic model. What we do exactly is to resort to the forward procedure for incorporating variables into a given DEA model as proposed in Pastor, Ruiz and Sirvent (1995). Basically we resort to a stepwise procedure which decides in each step whether it is necessary or not to incorporate a new variable to the model. In the first step we compare the efficiency scores of the basic model with the efficiency scores of each of the extended models obtained by adding one of the environmental variables to the basic model. For instance, if we start with a set of "q" environmental variables, then we have to make "q" comparisons. We compute, each time, the ratio of the efficiency scores of the basic model and the efficiency scores of the extended model and get a new set of scores, denoted by $\boldsymbol{\rho}$. We fix a tolerance limit for $\boldsymbol{\rho}$ and we consider that the proportion of units with $\boldsymbol{\rho}$ lower than the tolerance limit must be lower than a certain percentage of units in order to decide that the added variable is non-influential.

We perform a non-parametric statistical test, based on the binomial distribution in order to assert if there is statistical evidence to add the variable at hand to the model. For instance, if T is the number of units with $\boldsymbol{\rho}$ lower than the tolerance limit, the corresponding p-value will be given by [1-F(T-1)], being F the binomial distribution function corresponding to B(N,p). Where N denotes the number of units which can have a $\boldsymbol{\rho}$ lower than the tolerance limit and p denotes the fixed percentage of units. Pastor, Ruiz and Sirvent (1995) have shown that N is equal to the number of units in the sample minus the number of units with $\boldsymbol{\theta}$ greater than, or equal to, the tolerance limit. Here $\boldsymbol{\theta}$ represents the efficiency score of the basic model. If the p-value is zero or close to zero we have to reject the null hypothesis and admit that the added variable is influential. Otherwise, we stay with the basic model. Once a variable has been added in the first step we have to perform the second step in the same way. After a finite number of steps have been performed the procedure will stop[5]. We call the final model the “complete model”. The mathematical formulation of this model is:

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[4] See Banker and Morey, 1986.

[5] Banker (1996) has recently proposed several parametric tests for the specification of a DEA model. We preferred the proposal of Pastor et al. (1995) because it is distribution free and because it is a stepwise procedure.

$$\min_{\boldsymbol{\theta},\,\boldsymbol{\tau}} \boldsymbol{\theta} \text{ subject to} \quad \begin{aligned} Y\boldsymbol{\tau} &\geq Y_0 \\ Z\boldsymbol{\tau} &\geq Z_0 \\ X\boldsymbol{\tau} &\leq \boldsymbol{\theta} X_0 \\ e^T\boldsymbol{\tau} &= 1 \\ \boldsymbol{\tau} &\geq 0_n \,, \end{aligned}$$

where Z denotes the matrix of selected environmental outputs, and Z_0 the corresponding vector of the unit being rated. Observe that we consider all the environmental variables on the output side. This is because any non-discretionary input can be transformed into a non-discretionary output just by reversing its sign and translating it[6].

3. DATA AND VARIABLES

Data. In our empirical study, we use 1993 data of ten European banking industries for the definition of the banking outputs and inputs. The data were obtained from IBCA panel. The need to establish domestic as well as international comparisons, jointly with the availability of labor employment data, imposed certain restrictions in order to get a domestic and internationally homogeneous sample of banks in terms of specialization. In our international comparison we take into account only commercial banks and reject savings, public, industrial, development, as well as merchant banks.

The banking industry of Belgium, Denmark, France, Germany, Italy, Luxembourg, Netherlands, Portugal, Spain, and UK were analyzed. We ignored some small banks of each country banking industry, as well as the whole banking industry of several European countries, because of questionable data[7]. As a result, after carefully checking the data for consistency, we have usable data for 612 commercial banks belonging to ten European countries: 24 Belgian banks, 29 Danish, 150 French, 203 German, 26 Italian, 68 Luxemburgian, 22 Dutch, 17 Portuguese, 28 Spanish, and 45 English.

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[6] See Pastor (1996).

[7] Despite of having ignored several banks, the selected sample can be considered as representative, given that it includes almost all the banks classified as commercial banks in IBCA Ltd. We have eliminated only banks from France and Germany. In any case the percentage of eliminated banks was less than 3%.

The data for the definition of the environmental variables were gathered from Bank Profitability and Main Economic Indicators (OECD), Eurostat (Money and Finance), Anuario Estadístico del Instituto Nacional de Estadística (INE), and Boletín del Banco de España.

All variables presented in value terms of local currencies --including banking outputs and inputs as well as environmental variables--were converted into a common currency using the purchasing power parity hypothesis. We chose the US 1993 dollar.

Input and output variables. In the banking literature there has been considerable disagreement regarding the "proper" definition of inputs and outputs. We have adopted the value-added approach (Berger and Humphrey, (1992)) to identify banking outputs and inputs. In the value-added approach, all items on both sides of the balance sheet may be identified as inputs or outputs depending on their contribution to the generation of bank added value. In this sense, deposits as well as assets are considered to have some output characteristics: deposits provide for transaction and safekeeping output services and also add to input costs. In a value-added context, deposits typically account for over half of total capital and labor expenses at banks and so, in this sense, output services are clearly being produced. Accordingly, in this study we specify four outputs: y1=loans, y2=deposits[8], y3=other earning assets[9], and y4 =other funds; and two inputs: x1 = personnel expenses, and x2=non-interest expenses --other than personnel expenses--.

We define personnel expenses as labor input instead of the number of employees because of lack of data[10]. This approximation of the labor input may generate some controversy due to the presence of pooling prices and quantities. If market power did not exist in the labor market, this approach would even be the best one, since we could correct labor by productivity --reflected by wages--. However, if differences in wages are due to market imperfections, our measurement of labor might underestimate the efficiency levels of firms that are paying higher wages to their labor factor. Overall, the higher the segmentation of the labor market, the more biased are the efficiency scores.

[8] Deposits were defined as produced deposits (the sum of demand, savings, time, interbank and other deposits).

[9] Earning assets were defined as the sum of all existing deposits with banks, short-term investments, and other investments.

[10] For instance, as Berg et al. (1993) and, Grifell and Lovell (1995, 1996) did.

Table 1 shows total and average values of bank outputs and inputs, in common currency, for 1993. This information is presented for each country, separately, and for the total sample (Column 11) --the 612 commercial banks--. We observe enormous differences in the average values of portfolio loans and deposits between countries, although these are higher for the total value of deposits than for the portfolio loans. By comparing the differences between the maximum and minimum average value of deposits with the differences between the maximum and minimum average value of loan portfolio, the former is almost 40% higher than the latter. One reason could be the different strategies followed by each banking industry after the deregulation of the interest rates.

The input expenses by unit of output differ among countries. In particular, we observe that both the personnel and the non-interest expenses by unit of output (deposit) are much higher for some countries, around 80% higher.

We presume the proportion of inefficient banks within each country as an additional reason explaining the enormous differences presented in the average values of bank inputs and outputs across countries. Working with samples with this type of heterogeneity could lead to surprising results when measuring the efficiency scores.

Environmental variables. The environmental variables selected and used in this paper are macroeconomic variables as well as variables explaining the particular features of each countries' banking industry, such as economic and regulatory conditions, or the accessibility of banking services of each countries' banking industry. All these variables have the same value for all the banks of the same country.

The set of environmental variables selected is presented in Table 2. The first environmental variable is the income per capita of a country, IC --defined as the ratio between Gross National Product over the number of inhabitants--. IC affects numerous factors related to the demand and supply of banking services (mainly deposits and loans). Countries with higher IC are assumed to have a banking system operating in a mature environment and resulting in more competitive interest rates and profit margins. At the same time, the banking system could also exert more activity. The second environmental factor, SC, or salary per capita, has been taken as indicator of each country's economy performance. It is reasonable to hypothesize that banking systems operating in a riskier environment, i.e. irregular functioning of the economy as a whole, could obtain lower average efficiency level. The population density, PD, is measured by the ratio of inhabitants per square kilometers. We assume that financial services supply in

Table 1. Summary Statistic for Banking Outputs and Inputs, 1993

	Belgium	Demmark	France	Germany	Italy	Luxembourg	Netherlands	Portugal	Spain	U.K.	Total Sample
Outputs											
Loans (U.S. dollar)											
Total	110121417	56960743	788481196	718426915	441150265	51045631	112124449	38505839	179253048	83664752	2569432416
Average	4588392	1964164	5256541	3539049	16967318	750671	5096566	2265049	6401895	1859217	4198419
Deposits											
Total	281928208	96301334	1362424711	580776070	658526447	197718203	150616073	83638714	369841269	140187328	3903968097
Average	11747009	3320736	9082831	2860966	25327940	2907621	6846185	4919924	13208617	3115274	6379033
Other earning assets (U.S. dollar)											
Total	187219240	50973905	791178776	415878494	333084447	164516412	60310854	42165721	210883127	71774594	2317447753
Average	7800802	1757721	5274525	2048663	12810940	2419359	2741402	2480337	7531540	1594991	3786679
Other funding (U.S. dollar)											
Total	7562915	6388683	148298166	512831446	77269823	9850489	17041418	2197552	13753492	6652392	799875561
Average	315121	220299	988654	2526263	2971916	144860	774610	129268	491196	147831	1306986
Inputs											
Personnel expenses (U.S. dollar)											
Total	2039867	1141925	15103908	8198514	8958619	688247	2063536	1463227	4627146	2495411	46590121
Average	84994	39377	100693	40387	344562	10121	93797	86072	165255	55454	76128
Non-interest expenses (U.S. dollar)											
Total	3389865	1691035	19724361	13179646	12783058	732328	2202122	1520147	6871122	2652074	64487521
Average	141244	58312	131496	64924	491656	10770	100096	89420	245397	58935	105372

areas of low population density would impede banks to obtain high efficiency levels. The density of demand, DD, measured by the ratio of deposits by square kilometer, is assumed to be a relevant feature in determining efficiency. Banks that operate in markets with a lower density of demand incur in higher expenses. These four environmental variables reflect the main economic conditions in which banks exert their activities.

Income per branch, IB, and deposit per branch and DB are seen as usual measure of relative efficiency of the banking industries. We assume that the higher IB or DB, the higher will be the banking efficiency levels.

In the empirical literature, other studies have found that larger number of branches in a banking system has a negative contribution to efficiency growth because of the increasing in operating costs of providing banking services[11]. Additionally, banking systems with a higher ratio of branches by number of inhabitant, or branch per capita, BC[12], imply over dimension which works against efficiency. However, work done on this issue shows that to ignore the geographical dimension of the market where the banks operate might lead to an erroneous evaluation of the banking efficiency levels[13]. Therefore, we also define the ratio of number of branches by square kilometer, BD. This variable is used as a measure of branch density that takes into account the space dimension for each national market. Variable BD is assumed to have negative influence on the efficiency. Those variables refer to the accessibility of the banking services for customers.

Finally, we use the average capital and profitability ratios as indicators of countries banking industry regulatory and competitive conditions, respectively. The average capital ratio is used as a proxy of regulatory conditions and is measured by equity over total assets, EOTA. Usually, lower EOTA leads to lower efficiency levels, because less equity imply higher risk taken and greater leverage, which could result in greater borrowing costs. Finally, the profitability ratio is defined as average return over equity, ROE, and is used as an indicator of the competitiveness in each banking industry. The predicted relationship between ROE and efficiency is positive, i.e. the larger the profits, the higher the efficiency.

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[11] To give one example, Pastor, Pérez and Quesada (1997) used the number of branches as a measure of the convenience for, or the proximity to the customer in order to explain the poor performance of the efficiency levels across countries.

[12] The variable BC has been defined as branch per 10.000 inhabitants.

[13] See Fuentelsaz and Salas (1991).

The use of the environmental factor within DEA models requires knowing the oriented influence of the environmental variables. We define this influence by looking at the type of relationship between environmental variable and efficiency scores. If we assume that the higher (lower) the value of an environmental variable, the higher (lower) the efficiency scores, then we say that the environmental variable is output oriented. On the other hand, if the opposite relationship holds, we say that the environmental variable is input oriented[14]. Consequently, IC, SC, PD, DD, IB, DB, EOTA, and ROE would be classified as output oriented, while BC, and BD are input oriented. Following Cooper and Pastor (1996), the first 8 environmental factors must be introduced as non-discretionary inputs and the last 2 factors as non-discretionary outputs in a DEA model.

Table 2 contains the values of the environmental variables in 1993 for each European country. Overall, the values of these variables suggest large differences in terms of the particular economic, banking accessibility and regulatory conditions across countries.

Table 2. Summary Statistic for Environmental Variables by Country, 1993

	IC	SC	PD	DD	IB	DB	BC	BD	EOTA	ROE
Belgium	17130	30759	329.3138	5.1403	0.0088	9.5625	0.0017	0.5703	0.0398	0.0954
Demmark	16812	20617	120.4847	1.3945	0.0320	25.67	0.001	0.0543	0.0593	0.1061
France	17646	26964	105.9995	0.9689	0.0328	20.0462	0.001	0.0483	0.0427	0.0287
Germany	16777	24197	227.5326	3.2902	0.0256	61.9711	0.001	0.1259	0.0430	0.1379
Italy	16497	27038	189.4358	1.5369	0.0317	17.9591	0.0005	0.0856	0.0944	0.1111
Luxembourg	20538	28925	154.6551	55.1499	0.0324	466.1427	0.0008	0.1183	0.0260	0.1993
Netherlands	16061	27588	373.9067	5.6392	0.0296	32.3861	0.0005	0.1741	0.0428	0.1407
Portugal	10532	13425	107.1891	0.5611	0.0329	16.4165	0.0003	0.0342	0.1437	0.0661
Spain	12121	23022	77.4195	0.6538	0.0120	9.5020	0.0009	0.0688	0.0962	0.0376
U.K.	15422	23107	237.3547	1.9059	0.0689	40.6012	0.0002	0.0469	0.0395	0.1902

[14] We use the environmental variables as categorical variables in our DEA model. Therefore, those variables are organized as follows: a categorical input of the model corresponds to an output-factor. For the analysis of categorical variables in DEA see Banker and Morey (1986), and Cooper and Pastor (1996).

4. EMPIRICAL RESULTS

Individual country results. The results of the efficiency scores of each countries' banks, when considering its own national frontier, are presented in Table 3. They show that the average internal efficiency is low in France and Germany, and high in Spain, Italy, and Portugal. These results contrast significantly with the results obtained in other international studies. For instance, Pastor, Pérez and Quesada (1997) found very different average efficiency score levels across countries. Again, these differences appear when we compare our findings with the results obtained in a recent study by Dietsch and Lozano (1996). These authors found that French and Spanish banks were on average equally efficient in their respective countries. We will turn later to this question.

Given the efficiency results of Table 3, it is not possible to compare the differences in efficiency across countries due to the fact that we use different frontiers for each country. In other words, we are not comparing the banks of each country against the same standard. Therefore, in order to compare the banking efficiency differences across countries we have to measure efficiency scores relative to a common frontier.

Table 3. Efficiency Scores: Internal Efficiency by Country

	Average	Std.
Belgium	78.04	27.80
Demmark	71.46	16.90
France	37.93	29.20
Germany	51.45	26.80
Italy	85.62	12.20
Luxembourg	59.13	28.10
Netherlands	71.26	31.30
Portugal	85.50	17.40
Spain	82.05	15.70
U.K.	56.29	32.20

Results from the basic and complete model. For an international efficiency banking comparison, we first defined the common frontier following the traditional approach, i.e. building a common frontier by pooling the data set for the banks of all the countries and considering a DEA model with 2 banking inputs and 4 banking outputs. Table 4 shows a summary of the average efficiency score and of its standard deviations for each country, separately, by using the basic model, i.e. without taking into account the specific environmental conditions of each country. The results show that Luxembourg gets the highest average efficiency scores, around 52.5%, and Spain (Portugal) the lowest, around 19.4% (16.4%). These results contrast again with the results obtained by Dietsch and Lozano (1996) comparing the French and Spanish banks. This question will be examined later[15].

Table 4. Efficiency Scores: Basic Model

	Average	Std.
Belgium	42.51	28.50
Demmark	20.17	13.70
France	26.27	25.50
Germany	39.91	25.40
Italy	25.46	20.00
Luxembourg	52.47	26.40
Netherlands	40.05	28.70
Portugal	16.39	15.70
Spain	19.41	15.30
U.K.	23.41	22.20

Overall, the results show low average efficiency scores for each country. Although we are discreet with the results obtained up to now, they seem to be in accordance with our assumption that if the country-specific variables are an important factor in the explanation of the efficiency differences, then the basic model will generate too much inefficiency. For instance, when we observed the country-specific conditions from the raw data, we observed that, on average, the environmental conditions in Luxembourg were more satisfactory than in Spain; this fact could explain, at least partly, the differences in efficiency between both countries. The same is valid when making pairwise comparisons among the rest of the countries.

Therefore, in order to define properly the common frontier, we have to take into account the potential differences explained by the environmental factors. This procedure would allow us to prove whether the low average efficiency scores observed when we use a common frontier without environmental variables is due to a misspecification of the common frontier, or not. In order to define this common frontier we start with the selection of a proper subset of environmental variables.

[15] If we focus on the standard deviation and compare Table 4 with Table 3 can be detected a non-surprising effect: the standard deviations are small and approximately equal in Table 4 and Table 3, if we exclude Italy. That means that Italian banks are very heterogeneous.

We consider first the whole set of 10 environmental variables (see Table 2). Applying the technique explained in Section 2, we implemented a forward procedure in order to incorporate the least number of environmental variables into our basic model. The results of using this procedure are shown in Table 5. In a first step, we compared the efficiency scores of the basic model with the efficiency scores of an extended model obtained by adding to the basic model only one of the environmental variables, let us say variable IC (income per capita). We computed the ratio of the efficiency score of the basic model, and the efficiency score of the extended model, and got what we call $\boldsymbol{\rho}$. We fixed as tolerance limit for $\boldsymbol{\rho}$ the value 0.9 and we consider that the proportion of units with $\boldsymbol{\rho}$ lower than the tolerance limit must be lower than 10% in order to consider that variable IC is non-influential. For variable IC we obtained T=89 units with $\boldsymbol{\rho} < 0.9$. Since the basic model had 46 banks with $\boldsymbol{\theta}$ no lower than 0.9, we considered the binomial with N=612-46=566 and p=0.1 in order to assert if there was statistical evidence that lower than 10% of the banks had a $\boldsymbol{\rho}$ lower than 0.9. We found that the p-value associated with IC was 0 and so we had to reject the null-hypothesis. As a result, IC was an influential variable. In the same way we counted T for each of the ten models obtained by adding one of the ten environmental variables to the basic model. The results are summarized in column 2 of Table 5. We can observe that in the first step the two most influential variables are DD (deposit density) and DB (deposit per branch), with T=313 for both cases. The non-parametric binomial test offered us a p-value equal to 0 for these two variables, which means that we have to reject the null hypothesis and to accept that any one of the two environmental variables considered is influential. In order to solve the tie we further evaluated the mean value of the $\boldsymbol{\rho}$´s for each of the two extended models. We obtained an average of 0.816 for DD and of 0.828 for DB; consequently, the variable DD was incorporated to the model.

Table 5. Selection of Environmental Variables

	Step 1	Step 2	Step 3	Step 4	Step 5
	r<0.9	r<0.9	r<0.9	r<0.9	r<0.9
IC (Income per capita)	89	8	11	43	19
SC (Salary per capita)	87	37	51	141	
PD (Population density)	162	30	9	0	0
DD (Deposit density)	313				
IB (Income per branch)	88	101	79		
DB (Deposit per branch)	313	73	48	0	0
BC (Branch per 100000 inhabitant)	31	67	38	0	0
BD (Branch density)	34	63	37	2	3
EOTA (equity over total assets)	19	142			
ROE (Return over equity)	207	98	38	0	0

In the second step we started with the new 7 variable model and repeated again the same process of adding one of the nine remaining environmental variables to the new fixed model. In the same way we obtained the results showed in column 3 of Table 5. Here we had no doubt that the variable to be incorporated to the model was EOTA (equity over total assets), again with a p-value of 0, obtained by considering the binomial with N=612-72=540 and p=0.1. Table 5 shows that, by expanding iteratively our model, the next variable to be incorporated to the model was IB (income per branch) and then SC (salary per capita) in steps 3 and 4, respectively. In step 3, the binomial N=612-100=512 and p=0.1 offered a p-value for variable IB equal to 0.00008 and, in step 4, the binomial N=612-111=501 and p=0.1 offered a p-value for variable SC equal to 0.

Finally, in step 5 (see Table 4 again) the process finished because no further variable deserves to be included into the model. In fact, the most influential variable at this step, IC, has a T=19, which, resorting to the binomial distribution with N=612-123=489 and p=0.1, corresponds to an associated p-value equal to 1. Consequently, our complete model has 10 variables (2 basic inputs, 4 basic outputs and 4 more non-discretionary inputs corresponding to the environmental variables DD, EOTA, IB and SC).

The average efficiency scores obtained by means of the complete model are shown in Table 6. Comparing the new results with the average efficiency scores shown in Table 4 makes it easier to appreciate that the environmental variables appear to play an important role in the explanation of the differences of the banking efficiency between countries. When we introduce these variables into the model, the average efficiency scores improve significantly for all the countries. Even though, after carefully observing our results, one important point should be emphasized: if we compare the results of Table 6 with the results of Table 3, it is surprising that eight out of the ten countries reach exactly the same efficiency level, as well as the same standard deviation, in both Tables.

So, two features of the results obtained, until now, took our attention. The first interesting feature is the equality of average efficiency levels between the complete model and the individual frontier models for most of the countries. The reason of these results is that the inclusion of country-specific environmental variables acts to restrict the set of banks being compared to the same ones being compared when separate national frontiers were used (Table 3); hence the identical efficiency results for most countries. So, it appears that the classical treatment of non-discretionary variables in DEA is too strict. The second feature is that our results obtained from the individual frontier and from the basic model contrast with the results obtained in others studies, as we pointed above. Particularly, we observed that the larger the sample, the higher the difference in the results. This could be due to the fact that there are enormous divergences between the number of inefficient banks in different countries. Therefore, if we use samples with significant heterogeneity in terms of the number of inefficient banks, then our measure of efficiency scores could be distorted. The same conclusion could be reached by focusing only on Table 3. Looking at this table, it was hard to accept that the internal efficiency of Portugal and Netherlands, the two countries with the smallest samples (under 30 banks), was greater than 70% while the corresponding to Germany and France, the two countries with the biggest samples (over 150 banks), was under 52%. The conclusion was obvious: the country samples are non-homogeneous.

Table 6. Efficiency Scores: Complete Model

	Average	Std.
Belgium	78.04	27.80
Demmark	71.46	16.90
France	37.93	29.20
Germany	51.45	26.80
Italy	32.36	22.80
Luxembourg	59.13	28.10
Netherlands	46.43	30.30
Portugal	85.50	17.40
Spain	82.05	15.70
U.K.	56.29	32.20

The next step in our empirical exercise was to correct the two deficiencies observed in our results. We first tried to mitigate the influence of the non-discretionary variables in the efficiency scores. To do so, we defined the so-called "codified complete" model. Afterwards, we tried to avoid the influence of non-homogeneous samples on the efficiency scores. We decided to recall the last models as "modified" models.

<u>Results from the codified complete model</u>. We were able to mitigate the influence of the non-discretionary variables in the efficiency scores as follows. As the environmental variables showed slight variability[16], we codified these variables before introducing them into the basic model. This treatment differs somewhat from the procedure proposed by Cooper and Pastor (1996) about this issue, although pursues the same objective, i.e. to broaden the set of the comparable units for the countries which have the lowest values in each category.

[16] The environmental variables take only ten different values, one for each country, with small ranges.

In order to codify each of the four influential environmental variables, we decided to create three categories for each variable. Category 1 (3) corresponds to the countries with the largest (smallest) values of each environmental variable. The categorization process is based in our common sense; we include in each category all the countries whose differences in the values of the environmental variables are judged as acceptable. As a result, the countries belonging to each category do not present significant divergence among them in terms of the value of each selected environmental variable. The code assigned to each category for a certain environmental variable is exactly the minimum value of the variable over the subset of countries that belong to this category. To give but one example, variable SC has been codified as follows: value 30759 for all the countries belonging to category 1 (only Belgium), value 26964 for all the countries belonging to category 2 (which corresponds to the minimum value of France, Italy, Luxembourg and Netherlands), and value 13425 for all the countries of category 3 (Denmark, Germany, Portugal, Spain and UK). In the DEA analysis performed by means of the complete model, Portugal had the worst value (13425) for SC and, consequently, the banks of Portugal admitted as role models only banks of the same country. This explains why the average efficiency score assigned to Portugal via the complete model is exactly the same as the average efficiency score evaluated by means of the individual model. After doing the codification, Portugal is able to admit as role models banks from any of the countries of category 3, which means that the average efficiency score assigned to Portugal by means of the complete model with codified environmental variables is likely to be less than 85.5. The classification of each country in each of the three categories for each of the four environmental variables is given in Table 7, as well as the values assigned to each category.

Table 8 presents the average efficiency scores for each country obtained by means of the codified complete model. Comparing the average efficiency scores results shown in Table 6, with these new efficiency scores results we are able to appreciate that the efficiency scores of almost all the countries are lower. This is due to the fact that now each country is admitting as role models banks from other countries belonging to the same or higher category for each of the environmental variables. Furthermore, the conclusion obtained above about the role played by the environmental variables is also consistent here. When we compare Table 4 and 8 we appreciate again that the efficiency scores improve significantly for all the countries, but now we do not find that the efficiency scores of all the countries are the same as their internal efficiency scores except for the case of Spain and Denmark.

Table 7. Codification of the four Environmental Variables

	Category 1	Category 2	Category 3
SC (Salary per capita)	30759	26964	13425
	Belgium	France Italy Luxembourg Netherland	Denmark Germany Portugal Spain U.K.
DD (Deposit density)	55.1499	3.2902	0.5611
	Luxembourg	Belgium Germany Netherland	Denmark France Italy Portugal Spain U.K.
IB (Income per branch)	0.0689	0.0317	0.0088
	U.K.	Denmark France Italy Luxembourg Portugal	Belgium Germany Netherland Spain
EOTA (equity over total assets)	0.0944	0.0593	0.026
	Italy Portugal Spain	Denmark	Belgium France Germany Luxembourg Netherland U.K.

Table 8. Efficiency Scores: Codified Complete Model

	Average	Std.
Belgium	53.13	30.32
Demmark	71.46	16.87
France	33.83	27.43
Germany	49.64	26.23
Italy	31.35	21.57
Luxembourg	52.96	26.33
Netherlands	47.45	30.60
Portugal	48.94	21.27
Spain	82.05	15.74
U.K.	34.53	25.37

We still found very large differences between the efficiency scores of Spain and France and, consequently, our empirical exercise continued trying to solve the second deficiency observed in our results in relation with the non homogeneity of the country samples used.

Results from the modified models. In order to avoid the influence of the non-homogenous country samples in the efficiency scores, the procedure followed was to project each bank belonging to each country to its own national frontier. As a result, all the banks will be considered as if they were efficient in their respective countries. This last exercise is interesting because the best banks of each country are supposed to have the best technology of each country and consequently, if we assume that our DEA model accounts for the influence of the environmental variables, as we do, we are able to discover the countries with the best banking technology.

Because we are using an input oriented model, it was necessary to decrease the proportion of inputs used by each inefficient bank of each country in order to translate their original position to a new position on the Debreu-Farrell frontier[17]. Moreover, due to the fact that most of the banks required that this translation were achieved, --because there were more banks out than on the frontier--, we decided to recall the models as "modified" models, as we pointed above. So, we evaluate again the efficiency scores from the common frontier with and without codified environmental variables. To do that, we defined the modified complete model, and the modified basic model. Curiously enough, we have not modified the structure of the DEA models but the data set.

Table 9 presents the average efficiency scores by countries obtained by means of the modified basic model, i.e. the basic model working on the transformed set of DMUs. If we compare the results obtained from the basic model, Table 4, with those obtained from the modified basic model, Table 8, we observe large changes in terms of efficiency scores by countries. For instance, given that France, Germany and Luxembourg are the countries which account for a larger number of banks in their individual samples --150, 203 and 68 banks, respectively--we can expect here the deepest gap: while the basic model offers average efficiency scores of 26.27% , 39.91% and 52.47%, respectively, the modified basic model rises to 65.40%, 75.37% and 90.80%. Furthermore, the results obtained for France and Spain from the modified basic model are now consistent with the efficiency results obtained for these two countries in Dietsch and Lozano (1996).

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[17] We will work only with efficiency scores without taking into account the slacks because of their relative small size.

Table 9. Efficiency Scores: Modified Basic Model

	Average	Std.
Belgium	51.38	23.20
Demmark	26.54	12.70
France	65.40	14.20
Germany	75.37	17.30
Italy	28.22	19.80
Luxembourg	90.80	15.70
Netherlands	55.81	22.70
Portugal	18.82	16.10
Spain	22.15	14.20
U.K.	43.10	22.20

One important feature, coming from the comparison of the results presented in Table 4 and 9, is that the larger (smaller) the individual country sample, the wider (closer) is the gap between the average efficiency scores. These findings support our suspicion that the proportion of inefficient banks existing in each individual sample has a significant influence in the efficiency scores.

Table 10 shows the results of the modified complete model, with the modified sample and with codified environmental variable. It seems that when we work with the transformed set of DMUs, jointly with codified environmental variables, the efficiency scores results are more realistic.

Table 10. Efficiency Scores: Modified Complete Model

	Average	Std.
Belgium	64.03	21.44
Demmark	100.00	0.00
France	88.34	0.09
Germany	96.54	0.07
Italy	35.29	21.10
Luxembourg	91.80	15.64
Netherlands	65.89	21.50
Portugal	56.00	17.91
Spain	100.00	0.00
U.K.	62.96	19.95

Given now our attention to these two final models, if we compare the results in Table 9 with the results in Table 10, we observe that when we introduce the codified environmental variables in the modified basic model, the average efficiency scores improve significantly in each country. Moreover, we systematically observe that the worse the country-specific conditions, the most improvement in the average efficiency score. If we rank the countries, taking into account their average environmental conditions[18], --reflected only by the four environmental variables incorporated into the model-- we see that Luxembourg, Netherlands, Italy and Belgium take the first, second, third and fourth place, respectively. The average improvement in their efficiency scores is around 11%. Germany, France, Portugal and the UK take, on average, the same place in terms of their average environmental conditions, and the average improvement in their efficiency scores is around 20%. Finally, Denmark and Spain take the worst place in the ranking, and these countries see their efficiency scores improved, on average, in 76%. Therefore, these findings are in accordance with our suspicion that the environmental variables are an important factor in the explanation of the international banking efficiency differences.

Interestingly, the countries that reach an average efficiency scores of 100% are those with the worst environmental conditions, Denmark and Spain. This could mean that most of the inefficiencies found for these countries with the modified basic model are not due to some country-specific aspects of the banking technology, but to the environmental and regulatory conditions.

Overall, we are able to distinguish three groups of banks classified by countries: Denmark, Spain, Germany, Luxembourg and France have efficiency values between 100 and 88.3, Netherlands, Belgium, the UK and Portugal experience efficiency values between 65.9 and 56.0, while Italy stands alone with an efficiency value of only 35.3. We have performed a nonparametric Kruskal-Wallis test and found that there is statistical evidence that the three groups are different. We have also performed a pairwise comparison by means of the Mann-Whitney test and found that any pair of groups is different. Consequently our cross-country comparison is worth and we judge our last model as the best one for the comparison of the banking systems.

The expectations about the behavior of the environmental variables included into the model could help to explain why some countries appear to be significantly less efficient when their average efficiency levels were obtained from the modified basic model than from the modified complete model. At the same time, these expectations would also explain the differences in

[18] We rank each country in terms of each environmental factor by looking at the values that the environmental variables take in each country. First, we rank each country for each environmental factor from 1 to 10. If the environmental factor is an output (input) of the model and gets the higher (lower) value, then the country gets a rank-value of 1. Once we know which is the ranking for each country with regard to each environmental factor, we calculate their mean. This constitutes the rank values for each country.

efficiency across countries. For instance, Luxemburgian banks appear to be suffering the lowest costs and highest efficiency scores, Table 8. On the other hand, Spanish banks seem to be operating with the second lowest efficiency scores. For instance, the lower salary per capita, density of demand and income per branch in Spain compared to Luxembourg seem to be the main explanation of the lower efficiency level in Spain. If we consider the influence of these factors in the efficiency scores of Spanish banks, we see that, on average, they become even more efficient (100%) than the Luxemburgian banks (91.82), Table 9. The same type of comparison could be established for the rest of countries.

Therefore, the influence of the environmental variables seems to be as we expected. Introducing environmental conditions always implies an improvement in the average efficiency scores, depending of the average country-specific condition. This proves the effectiveness of the role of such variables.

5. CONCLUSIONS

A common frontier that incorporates the country-specific environmental conditions is defined in order to know how different or similar are current banking performances between ten European countries. This common frontier is built under the assumption that the environment is likely to differ more significantly across countries than the banking technology. That is, we claim that if international banking comparisons in efficiency do not consider country-specific environmental conditions, the banks of the countries with bad environmental conditions would get inefficiency values lower than expected, since they are not compared on an equal footing in relation to the banks from countries with good environmental conditions[19].

We try to verify this assertion by evaluating average efficiency scores for each European country from a common frontier with and without environmental variables using DEA. To do that, we define a DEA model called “complete model” which is the result of including the environmental variables of each country into a previously defined DEA model called “basic model”. We do not incorporate all the environmental variables but only the influential ones. The

[19] This is the case of the results obtained in previous international comparison studies in banking efficiency. See Berg, Førsund, Hjalmarson, and Suominen (1993), Fecher, and Pestieau (1993), Berg, Bukh, and Førsund (1995), Bergendahl (1995), Allen, and Rai (1996), and Pastor, Pérez and Quesada (1997).

selection is performed by means of a stepwise procedure. Considering the "internal efficiency" of each country, obtained by means of a DEA model which evaluates only the banks of that country, and comparing the results of the complete and basic models we conclude that the environmental variables are too influential and, in some sense, distort the efficiency results. For this reason we propose to codify the environmental variables and to reevaluate the efficiency of the different countries by means of the so-called "codified complete" model. Finally, our last exercise is to incorporate the banking technologies of the different countries on an equal footing. The internal efficiency of each country revealed to us that the country samples are rather different. Therefore, we modified the units of the sample by translating (if necessary) all the banks so as to deal with new "internal efficient units". Based on this new sample we defined the "modified basic" model as well as the "modified complete" model. We consider only efficient banks in each country. This last exercise is interesting because the best banks of each country are supposed to have the best technology of each country and consequently, if we assume that our DEA model accounts for the influence of the environmental variables, as we do, we are able to discover the countries with the best banking technology. Moreover, we will be dealing with homogeneous samples and we will get a better international comparison of the banking systems. The modified complete model allows us to make a fair comparison between the different banking systems.

Our results show that when the common frontier is defined without environmental variables, the average efficiency scores of the banks of each European country are lower than when these variables are considered. Therefore, we verify our assertion that neglecting these variables could induce an important misspecification of the common frontier and an overestimation of the inefficiency. This result is consistent with the results obtained by Dietchs and Lozano (1996) using a parametric frontier approach.

Overall, from the results obtained by using our preferred model, the modified complete model, we are able to distinguish three groups of banks classified by countries: (i) Denmark, Spain, Germany, Luxembourg and France have efficiency values between 100 and 88.3; (ii) Netherlands, Belgium, the UK and Portugal experience efficiency values between 65.9 and 56.0, while (iii) Italy stands alone with an efficiency value of only 35.3. We found that there is statistical evidence that these three country groups are different in terms of efficiency levels. Consequently, our cross-country comparison is worth and we judge our last model as the best one for the comparison of the banking systems.

Interestingly, the countries that reach an average efficiency scores of 100% are those with the worst environmental conditions, Denmark and Spain. This could mean that most of the inefficiencies found for these countries with the modified basic model are not due to some country-specific aspects of the banking technology, but to the environmental and regulatory conditions. So, the expectations about the behavior of the environmental variables included into the model could help to explain why some countries appear to be significantly less efficient when their average efficiency levels were obtained from the modified basic model than from the modified complete model. At the same time, these expectations would also explain the differences in efficiency across countries.

Finally, the results seem to suggest to us that the most efficient Spanish banks, as well as the most efficient Danish banks, are the most efficient banks in Europe, after taking into account the effects of the environmental variables. So, the competitive viability of Spanish banks in a more unified European banking market seems to be unquestionable.

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