CREDIT RISK AND EFFICIENCY IN THE EUROPEAN BANKING SYSTEMS: A THREE-STAGE ANALYSIS*

José M. Pastor

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Correspondencia a: José M. Pastor: Departamento de Análisis Económico, Universitat de València, Campus dels Tarongers, s/n, Ed. Departamental Oriental, Valencia (SPAIN), e-mail: jose.m. pastor@uv.es

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ABSTRACT

Increased competition and the attempts of European banks to increase their presence in other markets may have affected the efficiency and credit risk. The first of this aspects is based on the incentive to the banks to reduce cost in order to gain in competitiveness. The second is associated to their lack of knowledge of such markets and/or acceptance of a higher risk in order to increase their market share. Despite the importance of these aspects, banking literature has usually analyzed the effects of competition on the efficiency of banking systems without considering these aspects. The few studies that attempt to obtain risk adjusted efficiency measures do not consider that part of the risk is due to exogenous circumstances. This article proposes a new three stage sequential technique, based on the DEA model and on the decomposition of risk into its internal and external components, for obtaining efficiency measures adjusted for risk and environment. It is seen that the technique allows the use of any existing technique of incorporation of environmental variables in DEA analysis.

Key words: DEA, credit risk, bad loans, efficiency, environmental variables.

RESUMEN

El incremento de la competencia y los intentos de los bancos europeos por aumentar su presencia en otros mercados pueden haber afectado tanto al nivel de eficiencia bancaria como al riesgo de crédito. El primero de los aspectos se fundamenta en el incentivo que tienen los bancos a reducir los costes para ganar competitividad. El segundo, está asociado a la ausencia de competencia en tales mercados y/o a la aceptación de niveles mayores de riesgo con el fin de incrementar la cuota de mercado. A pesar de la importancia de estos aspectos, la literatura bancaria tradicionalmente ha analizado los efectos de la competencia en la eficiencia de los sistemas bancarios sin considerar estos efectos sobre el riesgo. Los escasos estudios que intentan obtener medidas de eficiencia ajustadas por el riesgo no consideran que parte del riesgo es debido a circunstancias exógenas. Este artículo propone una nueva técnica secuenciencial en tres etapas, basado en el modelo DEA y en la descomposición del riesgo en sus componentes externo e interno, para la obtención de medidas de eficiencia ajustadas por el riesgo y el ambiente. La técnica se aplica al análisis de la eficiencia de los sistemas bancarios europeos y permite el uso de cualquiera de las tecnicas existentes para la incorporación de variables ambientales en un contexto DEA.

Palabras clave: DEA, riesgo de crédito, morosidad, eficiencia, variables ambientales.

1. INTRODUCTION

The increased competition associated with the process of liberalization and globalization and the attempts of European banks to increase their presence in other markets may have affected the efficiency and credit risk of the European banking institutions. The first of these aspects, already analyzed in other studies, is based on the incentive to the banks to reduce costs and to improve the management of their resources in order to gain in competitiveness. The second aspect, which has not yet been analyzed, is explained by the poorer knowledge of the new markets by the newly entered banks and/or the greater permissiveness in the acceptance of risk with a view to increasing the market share in certain sectors and/or regions. Despite the importance of these two aspects, banking literature has usually analyzed banking efficiency without considering them together.

Traditional efficiency measures, based on the consideration of outputs and inputs, are usually a good instrument of analysis of the performance of firms; however, it is sometimes necessary to consider other factors. In the case of banking, one of the most important of these is risk, as it is desirable not only that a banking firm should be efficient, but also that it should be secure[1]. This is certainly not exclusive to the banking sector, but it is of greater importance than in other sectors, given the potential economic repercussions of banking failures. However, despite its importance, the relationship between risk and efficiency has hardly been studied in the literature. Only the studies by Berg et al. (1992), Hughes et al. (1993 and 1996) and Mester (1994a, 1994b) have attempted to obtain risk-adjusted efficiency measures. However, their approaches may be unsuitable insofar as they are based on the inclusion of risk (measured by means of total bad loans) as an additional input, implicitly assuming that all bad loans are caused by the bad management of banks, without considering that some may be due to adverse economic circumstances beyond the banks' control. If these exogenous or uncontrollable factors are not filtered out, the efficiency of those firms whose bad loans are due to an adverse economic environment will be underestimated. Furthermore, none of the existing studies attempts to decompose total bad

[1] Toevs and Zizka (1994) affirm that standard ratios, normally used by financial analysts as indicators of efficiency, do not consider risk. Furthermore, they affirm that to try to improve efficiency can be counter-productive, as banks may do so by transferring their activities towards high-risk business, with low operating costs and high profitabilities.

loans into these two components: bad loans due to bad management (internal factors) and bad loans due to economic environment (external factors)[2].

International comparisons of banking efficiency have not loomed large in the literature. The lack of homogeneous accounting data and the existence of different regulatory frameworks notably complicate these comparisons. The very few studies in this field, based on the construction of a common frontier for all countries, have traditionally found high degrees of inefficiency. This result may be due to the fact that the procedure used implicitly assumes that any difference of efficiency between countries is exclusively due to bad management, without also considering the possible existence of technological differences (Pastor, Pérez and Quesada, 1997) or differences in the economic environment (Pastor, Lozano and Pastor, 1997) which may bias the results and provide under-estimated efficiency measures for those banking systems that are subjected to less favorable economic environments. To avoid this problem it is necessary to introduce environmental variables to control for the different economic circumstances under which the banking firms of different countries carry out their activity. In this respect, the most notable exceptions are the recent studies by Dietsch and Lozano (1996) and Pastor, Lozano and Pastor (1997) which incorporate environmental variables with the aim of establishing a common standard of comparison for all firms. However, unlike parametric frontier models, the incorporation of environmental variables in DEA models is a field still being researched, offering a wide variety of proposals which have to be considered and compared.

In this context, and in order to solve these problems, this study proposes a new (three stage) sequential technique, based on the DEA technique, to identify and decompose the origin of bad loans and to obtain efficiency measures adjusted for risk and environment, more refined than those hitherto proposed in other studies, to allow analysis of how not only the evolution of efficiency, but also risk management, have responded to liberalization measures. The procedure proposed enables the total bad loans of each bank to be decomposed, in a first phase, into its two components: one part due to bad risk management and another due to exogenous economic and environmental factors. For this purpose we use various approaches for incorporating environmental variables into DEA, with the aim of

[2] Only Pastor (1999) and Saurina (1998) analyse the determinants of bad loans distinguishing between internal and external factors, though the latter does not use the results to decompose bad loans.

testing whether this leads to significant differences in the results. In the second phase, incorporating into the model only the proportion of bad loans due to bad management, we obtain the risk-adjusted efficiency measures. Finally, in the third phase, by incorporating economic environment variables, we obtain indicators of efficiency which, as well as being adjusted for risk, are adjusted for the economic environment. The results are used to determine the influence on efficiency of risk ("risk effect") and of environment ("environment effect").

The paper is organized as follows. The second section reviews the existing studies on risk and efficiency, the studies that analyze international comparisons of efficiency and the different proposals for incorporation of environmental variables into DEA. Section 3 lays out the methodology proposed for decomposing bad loans and calculating the risk management efficiency and the risk and environment-adjusted efficiency measures. This methodology allows the application of the different proposals for incorporation of environmental variables into DEA models. This section also describes the procedure for decomposing the overall efficiency measure into the risk and environment-adjusted efficiency, the risk effect and the environment effect. Section 4 describes the data used, section 5 gives the results, and finally section 6 presents the conclusions.

2. LITERATURE REVIEW

2.1. The relationship between risk and efficiency

There are many aspects in which credit risk (usually measured through bad loans, problem loans or provisions for loans losses) is related to efficiency. They have all been excellently analyzed by Berger et al. (1997) who find that there is a negative relationship between cost efficiency and risk in failed banks[3].

Berger et al (1997) offer several reasons for this negative relationship. First, inefficient banks, as well as having problems of controlling their internal costs, may have

[3] Other studies find that failed banks are usually cost inefficient (Berger et al., 1992; Barr et al., 1994; Wheelock et al., 1995 and Becher, et al., 1995), or that an increase in bad loans is usually preceded by an increase in cost inefficiency (De Young et al., 1994).

problems in the assessment of the credit risk, so that a bad management of costs goes together with greater credit risk. Berger et al (1997) call this origin of risk "bad management hypothesis". Second, bad loans may arise because of adverse economic circumstances beyond the bank's control, so that banks have to spend more resources to recover the problem loans. This origin of credit risk they call "bad luck hypothesis". Alternatively, there could be a positive relationship between cost efficiency and credit risk when banks decide not to spend sufficient resources on analyzing loan applications. In this way they would appear to be efficient but with a high level of bad loans. Berger et al (1997) call this "skimping hypothesis".

In spite of the extensive analysis by Berger et al. (1997), their procedure, based on the Granger causality test, does not enable the origins of risk to be found at individual level, but reaches very broad conclusions for the industry as a whole. Also, the conclusions will depend on the proportion of banks acting on each particular hypothesis, so the results obtained will always be underestimated because firms do not act uniformly[4]. Furthermore, as they themselves affirm, the Granger causality test measures statistical associations that in no way imply economic causation.

In the literature on banking there is no study that decomposes the origins of bad loans and, although some studies have attempted to obtain risk-adjusted efficiency measures[5], the method used is unsuitable for two fundamental reasons. First, these studies attempt to obtain risk-adjusted efficiency measures by introducing the measurement of credit risk (bad loans) directly in the model as an additional input. This procedure would characterize banks adequately only if bad loans originated <u>exclusively</u> in the "bad management" of risk. However, this situation is not reasonable, as the economic environment also influences banks' levels of bad loans, so that part of them is due to what Berger et al. (1997) call "bad luck". If what is wanted is to evaluate the efficiency of banks while controlling for risk, only the proportion bad loan caused by internal factors ("bad management") should be considered, while the proportion of bad loan caused by external factors ("bad luck") should be excluded.

[4] Berger and De Young find that some hypotheses are only consistent with sub-sets of data, as when the whole set of data is considered there is a mixture of effects.
[5] The first study was by Berg et al (1992) using the DEA technique. Subsequently Hughes et al. (1993 and 1996), Mester (1994a, 1994b) used parametric techniques.

Second, not all bad loans have the same probability of being recovered. The European central banks, following the European Union directives, regulate the provisions to be made in each particular circumstance. Therefore, given that these provisions are directly related to the probability of recovering the loans, it seems more appropriate to measure the risk by using the provisions for loans losses (*PLL*) instead of loans losses itself, as the first implicitly considers the risk associated with each problem loan.

Therefore, unlike the approach of Berger et al. (1997), which only enables generic conclusions to be reached, this study proposed a technique for identifying the causes of bad loan at individual level (using their terminology, "bad management" or "bad luck") and, unlike Hughes et al. (1993 and 1996) and Mester (1994a, 1994b) who obtain measurements of efficiency adjusted for risk by considering total bad loans, this study only incorporates that proportion caused by internal factors ("bad management"). The method proposed is applied to the commercial banks of the principal European banking systems with the aim of analyzing how the efficiency of banking firms and their behavior have evolved in the face of the risk implicit in the creation of the Single Market and the processes of de-regulation.

2.2. International comparisons of banking efficiency

International comparison of banking efficiency, although it has been researched before, has not loomed large in the literature. The only studies[6] are those by Berg et al., Førsund, Hjalmarson and Suominen (1993), Berg, Bukh and Førsund (1995) and Bergendahl, (1995), who compare the efficiency of the banking systems of the Scandinavian countries, Fecher and Pestieau (1993) who applied free distribution frontier techniques to the analysis of eleven countries of the OECD, Pastor, Pérez and Quesada (1997) who applied the DEA technique and the Malmquist index to the analysis of the efficiency and productivity of eight countries of the OECD, Allen and Rai (1996) who used the free distribution and parametric stochastic frontier techniques to compare the efficiency of fifteen developed countries, Dietsch and Lozano (1996) who used a parametric frontier to test whether the technology of the French and Spanish banking systems is similar when environmental variables are considered, and Pastor, Lozano and Pastor (1997) who analyze the efficiency filtered for environmental factors of ten community countries.

[6] See Berger and Humphrey (1997).

With the only exception of Pastor, Pérez and Quesada (1997), all these studies share the characteristic of being based on the construction of a common frontier for all countries and assume, at least implicitly, that the differences of efficiency among banking systems are due only to differences in management. Nevertheless, it is possible that the technology underlying the production of banking services may be different, and that the differences in efficiency reflect the existence of different technologies, as shown by Pastor, Pérez and Quesada (1997) or alternatively it is possible that the technology may be very similar, so that the efficiency is in fact reflecting differences specific to the environment of each country, as shown by Dietsch and Lozano (1996) and Pastor, Lozano and Pastor (1997). If this is so, i.e. if there exist important differences in the environment, the construction of a common frontier that does not consider these differences will generate underestimated measurements of efficiency, because efficiency would not only be incorporating bad management but also the existence of an unfavorable environment. Indeed, except for the cases where very similar banking systems are being analyzed (Berg et al., 1993 & 1995), the measurements of efficiency obtained are usually very low.

One way of solving these problems, without having to resort to the construction of a specific frontier for each banking system, is to consider a homogeneous line of banking business in order to ensure that the technology of the banks specializing in that business will be similar, and to incorporate environmental variables in order to guarantee that the comparison will be made considering exclusively firms subject to a similar environment[7].

Thus, in this study, as in Pastor, Pérez and Quesada (1997) and Pastor, Lozano and Pastor (1997), only banks specializing in commercial bank business are considered, and as in Dietsch and Lozano (1996) and Pastor, Lozano and Pastor (1997) a set of environmental variables are considered.

[7] Pastor, Pérez and Quesada 1997) use only commercial banks, Pastor, Lozano and Pastor (1997) likewise use commercial banks and incorporate environmental variables. However, in both cases the heterogeneity of the sample is still high, and consequently the measurements of efficiency are still very low.

2.3. DEA Model: Incorporation of environmental variables into DEA models

Measurements of efficiency in traditional DEA models are obtained by solving N problems of the type (Banker et al., 1984):

$$[1] \quad \begin{aligned} & Min_{\vartheta,\lambda} \quad \vartheta_j \\ & \sum_{i=1}^{N} \lambda_i y_{ri} \geq y_j; \quad r = 1,\ldots,R \\ & \sum_{i=1}^{N} \lambda_i x_{si} \leq \vartheta_j x_j; \quad s = 1,\ldots,S \\ & \sum_{i=1}^{N} \lambda_i = 1; \lambda_i \geq 0; \quad \forall i \end{aligned}$$

where $y_i = (y_{1i}, y_{2i}, \ldots, y_{Ri})$ is the vector of R outputs, $x_i = (x_{1i}, x_{2i}, \ldots, x_{Si})$ is the vector of S inputs. Solving the above problem for each of the N banks we obtain N optimum solutions. Each optimum solution ϑ_j^* is the efficiency measure of bank j and, by construction, satisfies $\vartheta_j^* \leq 1$. Those banks with $\vartheta_j^* < 1$ are considered inefficient, while those with $\vartheta_j^* = 1$ are considered efficient[8].

Unlike parametric models, in which incorporation of environment variables is direct, since they entry as additional explanatory variables, in DEA this is a field in which research is still being done and about which there is no consensus. The problem arise because there is not information about the negative or positive influence of each environment variable, in other words, the researcher does not know if a given variable should be considered as output or as input. The proposals are very varied (Rouse, 1996) and can be classified into methods of one, two and three stages.

The one-stage approach is the most direct and most easily interpreted, and consists of considering together outputs, inputs and environmental variables, restricting the problem of

[8] From an intuitive point of view, to analyse the efficiency of the productive scheme of firm j (y_j, x_j) the problem constructs a feasible scheme as a linear combination of the schemes of the N firms of the sample which, using $\vartheta_j x_j$ inputs produce at least y_j. In this way, $(1-\vartheta_j)$ indicates the maximum radial reduction to which the input vector of firm j can be subjected without altering the observed levels of input, so that ϑ_j is the indicator of technical efficiency. In the event that $\vartheta_j=1$, what occurs is that t is not possible to find any linear combination of firms which, with less input, obtains at least as much output, so that the firm is catalogued as efficient. In the other cases, $\vartheta_j<1$, indicating that the productive scheme followed by firm j is inefficient, since another feasible alternative scheme exists which obtains the same amount of output using $\vartheta_j x_j$ input, quantifying its overuse of resources in comparison with the alternative scheme as $(1-\vartheta_j)x_j$.

optimization to only the outputs and/or inputs. This method, proposed by Banker et al. (1986a & 1986b), has the aim of limiting the field of comparison to only those units of decision subject to equal or worse environmental conditions. However, despite being easy to interpret and to apply, it poses three fundamental problems: 1) the influence of each environmental variable has to be known *a priori* in order to orientate its influence on the optimization; 2) Those units of decision in worse condition are, by definition, considered to be efficient; and 3) the number of efficient units grows with the number of environmental variables introduced (restrictions)[9].

The commonest two-stage method consists of regressing in a second stage the indices of efficiency obtained in the first stage against the set of environmental variables[10]. It has usually been criticized for the fact that the indices of efficiency generated are not contained in the interval (0,1]. However, this criticism is groundless if we apply limited dependent variable models (Tobit) or simply regress an exponential function in order to prevent predictions above unity[11]. The advantages of this procedure are: 1) easy implementation; 2) possibility of considering many environmental variables simultaneously without increasing the number of efficient units; 3) there is no need to know the orientation of the influence of each environmental variable; and 4) possibility of use when some (or all) of the environmental variables are common to sub-sets of individuals.

Lastly, Fried and Lovell (1996) propose a three-stage method. In the first stage they propose using a DEA model with inputs and outputs. In the second stage, they include the slacks obtained in the first stage and the environmental variables in a stochastic frontier

[9] The first problem is not usually very important, as on most occasions the influence of the environmental variables is well known. However, the second problem is especially serious in those cases where a broad set of individuals share the same environmental conditions, as in this case this whole sub-set would be considered efficient. Pastor, Lozano and Pastor (1997) propose a solution to this problem, consisting of grouping the environmental variables into intervals in order to widen the field of comparison. Ray (1988), Golany et al. (1993) and Cooper et al. (1996)

[10] The first to apply this technique was Timmer (1971). After him, limited dependent variable models have been used profusely (McCarty et al., 1993). This procedure has traditionally been used to explain differences in efficiency rather than to filter their impact.

[11] An alternative two stage method is that of Pastor (1995b). This method is based on the application of DEA only to inputs (or outputs) and to the environmental variables in a first stage. In the second stage Pastor (1995b) proposes radial expansion of the inputs (or outputs) top eliminate the effect of the environmental variables. The procedure, though it has the advantage of generating predictions contained within the interval (0,1], presents the disadvantage that in the first stage outputs are not considered, and firms that use more inputs are assumed to do so because of unfavourable circumstances, without considering that it is because they produce more output.

approach (SFA) model or in a DEA model. The aim is to obtain slacks filtered for the influence of the environmental variables. These filtered slacks are used to adjust the inputs (and/or outputs) which will be used in the third stage to obtain the definitive indices of efficiency filtered for the environmental variables. It is not clear whether the high cost of this method in terms of time and computation requirements is compensated by a notable improvement in the results. Only the stochastic frontier version, by incorporating randomness, could present certain virtues in comparison with other methods.

In order to test the virtues and disadvantages of each of these methods (see table 1), in this study all of them are used and compared.

3. METHODOLOGY

3.1. Phase 1: Risk management efficiency and decomposition of bad loans

It has been shown in previous sections that bad loans can appear due to two different causes: internal and external. Given that external causes are beyond the control of the firms, the efficiency measure in the management of risk must be calculated by eliminating the effect of these external factors on bad loan.

This section describes the method, based on the DEA technique and on the incorporation of environmental variables, for estimating efficiency in risk management and decomposing our measurement of credit risk (*PLL*) into the part due to internal factors associated with bad management and the part due to external factors. The procedure consists of comparing each bank with a linear combination of banks which, with an equal (or higher) volume of loans, have a smaller (or equal) amount of *PLL* given the environmental conditions. The proposed technique enables the use of any of the existing techniques of incorporation of environmental variables into DEA. Since allowance is made for the environment (or the state of the economy) the indicator of efficiency obtained (γ_j) indicates the potential reduction of *PLL* that could be achieved without reducing the total amount of loans granted, given the existing state of the economy. We call this measurement "risk management efficiency" because it measures the proportion of bad loans (measured by

Table 1: Methods to include environmental variables in a DEA model.

Method	1 Stage	2 Stages	3 Stages	Advantages	Disadvantages	References
1 Stage	Incorporate environmental variables together with inputs and outputs in order to limit the comparison to the units that are subject to equal or worse environmental conditions.			1) Easily applied, 2) Easily interpreted. 3) Speed.	1) The influence of each variable must be known a priori. 2) Problems caused when some (or all) variables are common to sub-sets of individuals. 3) The number of efficient units increases with the number of environmental variables introduced.	Banker et al (1986a y 1986b), Lozano et al. (1996), Ray (1988), Golany et al. (1993), etc.
2 Stages	The DEA model only considers inputs and outputs.	The efficiency indices obtained in stage 1 are regressed using an OLS, Tobit or non-linear logistic regression.		1) Easily applied. 2) Easily interpreted. 3) Speed. 4) Can be used when some (or all) of the variables are common to sub-sets of individuals. 5) Variables can be introduced without increasing the number of efficient units. 6) Does not require the orientation of the environmental variables to be known beforehand.	1) If OLS is used in the second stage, the efficiency indices may not be contained within the interval (0,1].	Timmer (1971), McCarty et al. (1993), etc.
3 Stages (SFA)	The DEA model only considers inputs and outputs.	The slacks are regressed against the environmental variables using a stochastic frontier approach (SFA) in order to obtain slacks with the environmental effect filtered out. Those firms that obtain efficiency scores of less than one are in a favourable environment and inputs are therefore adjusted (increased) by that proportion to filter out the environmental effect	The inputs, corrected for environment, and the outputs, are used in the final DEA model.	1) Incorporates randomness into DEA. Very important in cases where there may be outliers. 2) Can be used when some (or all) of the variables are common to sub-sets of individuals. 3) Variables can be introduced without increasing the number of efficient units. 4) Does not require the orientation of the environmental variables to be known beforehand.	1) A very time-consuming procedure. 2) Large number of problems to be solved and high computation requirements. If N = number of firms, the number of problems is N*2.	Fried et al. (1996), Rouse (1996).
3 Stages (DEA)	The DEA model only considers inputs and outputs.	The slacks, treated as inputs, together with the environmental variables are incorporated into a DEA model in order to obtain efficiency indices that reflect the effect of environmental variables. Those firms that obtain efficiency indices of less than one are in a favourable environment and inputs are therefore adjusted (increased) by that proportion to filter out the environmental effect.	The inputs, corrected for environment, and the outputs, are used in the final DEA model.	1) Can be used when some (or all) of the variables are common to sub-sets of individuals.	1) The influence of each environmental variable must be known a priori. 2) Large number of problems to be solved and high computation requirements. If I = number of inputs and N = number of firms, the number of problems is N*(2+I).	Fried et al. (1996), Rouse (1996).

means of the *PLL*) that is attributable to bad risk management. If a particular firm *j* has an indicator $\gamma_j=1$ it means that there is another firm (or linear combination of firms) that grants an equal or greater amount of loans with a lower degree of bad loan $(1-\gamma_j)PLL_j<PLL_j$ [12].

This indicator of "risk management efficiency" (γ_j) can be obtained by any of the three methods described before which will now be set out in greater detail.

3.1.1. Single stage method

The indicator of "efficiency in risk management" (γ_j) is obtained in the single stage methods by solving the following problem for each bank *j*, with variable returns to scale (VRS):

$$
[2] \quad
\begin{aligned}
& Min_{\gamma,\lambda}\gamma_j \\
& \sum_{i=1}^{N}\lambda_i PLL_i \le \gamma_j PLL_j \\
& \sum_{i=1}^{N}\lambda_i L_i \ge L_j \\
& \sum_{i=1}^{N}\lambda_j Z_{pi}^{+} \le Z_{pj}^{+};p=1,..,P \\
& \sum_{i=1}^{N}\lambda_j Z_{qi}^{-} \ge Z_{qj}^{-};q=1,...,Q \\
& \sum_{i=1}^{N}\lambda_i = 1;\lambda_i \ge 0;\forall i
\end{aligned}
$$

in which N is the number of firms *(i=1,..,N)*, λ_i is the vector of weights, PLL_i is the provisions for loans losses, L_i is the volume of loans, and $Z_i^{+}=\left(Z_{1i}^{+},Z_{2i}^{+},\dots,Z_{Pi}^{+}\right)$ and $Z_i^{-}=\left(Z_{1i}^{-},Z_{2i}^{-},\dots,Z_{Qi}^{-}\right)$ are the vectors of environmental variables (economic cycle) with positive or negative influence respectively[13].

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[12] Note that greater inefficiency in the management of risk may reflect a lower aversion to risk on the part of firms, so that certain firms may prefer to accept a lower probability of repayment of the loan provided they obtain a higher rate of interest. In any case, the indicator obtained here measures firms' implicit risks, whether due to bad management or to reduced aversion to risk.

[13] Environmental variables are treated in the model as inputs or outputs by inverting their influence. Thus, for example, if an environmental variable has a positive influence (more means better) it is considered as input in the model (see Cooper et al, 1996). Note that all the environmental variables are treated as non-discretional variables (see Banker et al, 1986a).

3.1.2. Two-stage method

In the first stage of two stage models, the indicators of "risk management efficiency" (γ_j) are obtained by calculating efficiency indices without correcting for environmental variables (γ_i^{SC}) on the basis of the following problem:

$$
[3] \qquad \begin{aligned}
& Min_{\gamma^{SC},\lambda}\gamma_j^{SC} \\
& \sum_{i=1}^{N}\lambda_i PLL_i \le \gamma_j^{SC} PLL_j \\
& \sum_{i=1}^{N}\lambda_i L_i \ge L_j \\
& \sum_{i=1}^{N}\lambda_i = 1; \lambda_i \ge 0; \forall i
\end{aligned}
$$

In the second stage these uncorrected efficiency indices are regressed, taking the environmental variables (Z) as independent variables. In order to contain the efficiency indices within the interval (0,1], either a Tobit model or a logistic regression model can be used. In the latter case a non-linear regression should be performed as follows:

$$
[4] \qquad \gamma_i^{SC} = \frac{\exp(Z_i;\beta)}{1+\exp(Z_i;\beta)} + \varepsilon_i
$$

The predictions of the regression model would be the definitive efficiency indices adjusted for environmental variables which in our case would be the indicators of "efficiency in risk management" (γ_j).

3.1.3. Three-stage methods

The three-stage method is based on obtaining the slacks resulting from problem [3]. These slacks (s_i) are calculated as the difference between the optimum values and the real values for each firm, $s_j = \sum_{i=1}^{N}\lambda_i PLL_i - PLL_j$ In the second stage the slacks are filtered for environmental variables using a stochastic frontier model (SFA) or a DEA model. In the first case Fired et al (1996) proposed adding the corrected slacks to the original inputs, in our case to the *PLL*, and incorporating them into the third stage of the conventional DEA model. If DEA is used, the slacks obtained in the first stage are included with the environmental variables in the second stage to obtain corrected inputs, in our case the corrected *PLL*. In the third stage the corrected inputs, in this case the corrected *PLL*, are included in the final DEA model. For greater detail see the appendix.

In all cases the optimum solution, γ_j offers the proportion of *PLL* that bank *j* could reduce if it improved its risk management without altering the amount granted in loans. If γ_j=1 it means that there is no bank or linear combination of banks which with equal (or greater) amount of loans, and given the environmental conditions, has a lower volume of *PLL* than bank *j*. In this case, all the *PLL* would be due to external factors and bank *j* would be efficient in risk management, even though it had a certain degree of risk (*PLL*) as this would originate in the unfavorable economic conditions. In general, $\gamma_j \leq 1$, lower values of γ_j mean lower proportions of PLL due to internal factors, so that γ_j represents the proportion of PLL of bank *j* that is due to external factors and 1-γ_j is a measurement of the proportion due to internal factors.

3.2 Phase 2: Efficiency adjusted for risk

However, these traditional measurements of efficiency ϑ_j do not consider risk. If we wish to consider risk, as well as efficiency, to evaluate the performance of firms, it is necessary to "reward" (by increasing efficiency) those banks that are good managers of risk. For this purpose, Hughes et al (1993 and 1996) and Mester (1994a, 1994b) incorporated total bad loan as a measurement of firms' risk management. However, for the reasons given above, this measurement may be contaminated by economic shocks exogenous to the firms, which must be discounted so as not to penalize banks that are subjected to an adverse environment. In this study it is proposed to incorporate only that part of bad loan that is due to internal factors or bad management[14]. More specifically, given that γ_j measures the efficiency of risk management and *(1-γ_j)* measures the proportion of bad loan which is due to bad risk management, it is obvious that *(1-γ_j)PLL_j* measures the volume of *PLL* that is due to the risk policy of the firm (internal factors). Therefore, the efficiency measure adjusted for risk would be obtained by solving the following problem:

[14] Note that we include the PLL due to bad management and not the totals as in other studies.

$$
[5] \quad \begin{aligned}
&Min_{\rho,\lambda}\, \rho_j \\
&\sum\nolimits_{i=1}^{N} \lambda_i y_{ri} \geq y_j ; r = 1,\ldots, R \\
&\sum\nolimits_{i=1}^{N} \lambda_i x_{si} \leq \rho_j x_j ; s = 1,\ldots, S \\
&\sum\nolimits_{i=1}^{N} \lambda_i (1-\gamma_i) PLL_i \leq (1-\gamma_j) PLL_j \rho_j \\
&\sum\nolimits_{i=1}^{N} \lambda_i = 1; \lambda_i \geq 0; \forall i
\end{aligned}
$$

in which only the part of *PLL* due to internal factors, $(1-\gamma_j)PLL_j$ (obtained in phase 1 by any of the procedures described) have been included. The efficiency measure adjusted for risk ρ_j is a more suitable measurement of banking firms' performance than those of Berg et al (1992), Hughes et al. (1993, 1996) or Mester (1994a, 1994b), as it only penalizes those banks whose bad loans are due exclusively to bad risk management.

Comparison of the efficiency measure not adjusted for risk (ϑ_j) obtained in problem [1] with the efficiency measure adjusted for risk (ρ_j) obtained in problem [5] offers a measurement of the impact of risk management on the efficiency of banking form *j*, i.e. this comparison is a measurement of the "prize" or "penalty" in the efficiency measure awarded to it depending on how it manages risk**.** We call this impact the "risk management effect" (*RME*) and it is obtained from the following ratio:

$$
[6] \quad RME_j = \frac{\vartheta_j}{\rho_j}
$$

If a bank has *RME<1* this means it manages risk well, takes few risks and consequently has "won a prize" in terms of a efficiency measured adjusted for risk (ρ_j) higher than the unadjusted measure (ϑ_j). If, on the other hand, *RME=1*, it means that adding risk to the model has no effect on efficiency since the banks manage risk as well as better than other inputs[15].

---

[15] Note that the risk effect is always less than or equal to unity, meaning that the added restriction benefits the indices of efficiency or leaves them as they were. However this does not necessarily occur in the other procedures.

3.3 Efficiency adjusted for risk and environment: Phase 3

Although measurements of efficiency adjusted for risk (ρ_j) offer a more suitable evaluation of firms' performance, further refinement is still required, as the environment in which firms carry out their activity influences efficiency, sometimes decisively. To achieve a efficiency measure in which all firms are evaluated by the same standard, it is necessary to refine the efficiency measure adjusted for risk by including other environmental variables. This efficiency measure adjusted for risk and the environment (Ω) would be obtained by incorporating the effect of environmental variables by any of the procedures described earlier, with two reservations: 1) Now instead of PLL all inputs have to be corrected, and 2) the environmental variables that influence bad loan are not necessarily the same as those that influence efficiency.

The optimum solutions that include risk and environment will provide measurements of efficiency adjusted for risk and environment (Ω_j). As before, the ratio between the measurements of efficiency adjusted for risk (ρ_j) and the efficiency measures adjusted for risk and environment (Ω_j) offer us information on the degree of influence of the environment on the efficiency of the banks. We call this coefficient the "environment effect" (*EE*) and it is expressed as follows:

[7] $$EE_j = \frac{\rho_j}{\Omega_j}$$

If $EE_j < 1$, this means that the environment is unfavorable for the firm, as when it is compared only with the set of firms that are subject to the same conditions or worse, the efficiency measure improves. If, on the other hand, $EE_j > 1$, this means that the efficiency measure has penalized the firm, since the unadjusted measurements of efficiency attributed to efficiency what in fact was only a favorable environment[16].

Reformulating the above expressions, it is possible to decompose the efficiency measure with variable returns to scale of bank *j* into several components:

[16] Note that, unlike the risk effect, except in the single stage models, the environment effect may be a risk greater than unity.

[8] $\vartheta_j = \Omega_j \frac{\rho_j}{\Omega_j} \frac{\vartheta_j}{\rho_j} = \Omega_j EE_j RME_j$

Expression [8] offers information on the origins of the efficiency measure under VRS (ϑ_j), so that this can be explained in terms of the efficiency measure adjusted for risk and environment (Ω_j), of the environment effect (EE_j) and of the risk management effect (RME_j).

4. DATA AND VARIABLES

International comparisons of efficiency must be very careful in the selection of data. Not only the possible accounting heterogeneity of the variables used has to be considered, but also the different specializations and the different environment. In this study the data base was obtained from IBCA Ltd., an international rating agency which homogenizes the information and classifies firms in terms of specialization, so that the accounting uniformity is guaranteed. Homogenization of specialization was achieved by considering only commercial banks, therefore excluding other categories such as savings banks, state-owned banks, industrial and development banks, etc.

Since the key variable of the analysis is the provisions for loans losses (*PLL*) only those countries that report this variable as a separate item from other provisions could be selected[17]. This limits the analysis to Spain, Italy, France and Germany[18]. The total sample consists of 2598 observations from 1988 to 1994: 1144 observations of French commercial banks, 387 Italian, 524 Spanish and 543 German. In the case of Germany, due to the lack of PLL data the period studied is 1992-1994.

Inputs and outputs. In the banking literature there is no general agreement as to the proper definition of inputs and outputs. In this study, as in Pastor (1995a, 1996), Pastor, Pérez and Quesada (1997) and Pastor, Lozano and Pastor (1996), we opted to use the "value added"

[17] Unfortunately, information about loan losses is available only for a very small sample of banks. This fact makes impossible the comparison of the results obtained using PLL with those obtained using loans losses, which is the variable often used in the literature.

[18] Although only four countries form the European Community are considered, the sample chosen represented in 1994 59.8% of the total assets of the European Community's commercial banks.

approach (Berger and Humphrey, 1992) and selected three outputs: y_1=loans, y_2=deposits, y_3=other earning assets; and two inputs: x_1=personnel expenses and x_2=operating costs (excluding personnel expenses and including financial costs).

Environmental variables[19]: The environment variables were selected for their influence both on bad loan and on efficiency. *A priori*, only economic cycle variables influence bad loans, whereas other structural variables influence efficiency. With regard to the former, it was assumed that greater variability of the economic cycle has a positive influence on bad loan. To capture this influence the inter-annual coefficient of variation of nominal GDP was considered. Likewise, a higher growth rate of GDP has a negative influence on bad loan, so both the annual growth rate of GDP and the cumulative growth rate were included. These three variables were introduced with different lags and the recursive procedure in Pastor (1995b) was used to determine which variables are most influential. The results of this procedure determined that the most influential variables are the coefficient of variation of the nominal GDP of the period, the growth rate of nominal GDP of the period, and cumulative annual growth rate in the last 5 years.

The selection of variables influencing efficiency is, *a priori,* a much more complicated task because of the wide range of possibilities. To limit the possibilities in this study we consider initially the environmental variables that were found by Pastor, Lozano and Pastor (1997) to be influential, using the procedure in Pastor (1995b): *per capita* wages, density of deposits, national income per branch and capital adequacy ratio[20].

5. RESULTS

5.1 Risk management efficiency and decomposition of bad loans

The results obtained with regard to risk management efficiency, incorporating the environmental variables indicated above and using the different versions, are presented in

[19] The data on environmental variables is taken from the Economic Bulletin of the Bank of Spain, Bank Profitability, Eurostat and INE (National Statistical Institute of Spain). All the variables were expressed in dollars. See Freixas et al. (1994) for the macroeconomics determinants of loan losses.

[20] Pastor, Lozano and Pastor (1997) initially considered the following variables: income *per capita*, wages *per capita*, population density, density of demand, income per, deposits per branch, branches per inhabitant, branches per square kilometre, capital adequacy ratio and average profitability of the sector.

figure 1. The evolution of risk management efficiency of each of the countries is very similar in all techniques, with the sole exception of the one stage method (represented on the right-hand axis)[21].

Excluding the one stage method because of its limitations in this particular case, it can be concluded that efficiency in risk management has evolved differently in each country. While in Italy and Germany it has evolved without a particular trend, France shows a reduction in the risk management efficiency. In the case of Spain, after a descent of risk management efficiency during the period 1990-92, it appreciably improved, and by 1994 was at levels higher than in 1988. In general, the average portion of *PLL* due to internal factors stands at between 13% and 26%. Spain and Germany are the most efficient countries in risk management, with an annual average among methods of around 26% followed by France with 18% and Italy with 13%.

On the basis of the evolution of efficiency in risk management, instead of the overall evolution of bad loans, the conclusions on the evolution of risk in banking systems are very different. Thus, although bad loan has increased since 1990 in all countries (graph 1.i), bad loan due to risk management, with the exception of France where it worsens, either improves (Spain) or remains steady (Italy and Germany). It is possible, therefore, to conclude that the increase in competition generated by Community de-regulation processes does not seem to have pushed firms into riskier business and/or behavior.

Table 2 shows the values of the proportions of bad loans *(PLL)* attributed to internal factors $(1-\gamma_i)$ in each of the methods, excluding the single stage method. Obviously those banking systems that are less efficient in risk management have higher proportion of bad loan due to internal factors. Thus, for the case of Italy the proportion of bad loan due to internal factors is 87%, whereas in other banking sectors such as those of Spain or Germany these proportions are lower (around 73%).

[21] In the final instance, given that the environmental variables are common to all the firms of the same country, it is sufficient for a particular country to have a more unfavourable environment in one particular variable for all the firms of that country to be considered efficient. In the extreme case in which each country has an unfavourable situation in one of the environmental variables considered, all the firms of all the countries will be considered efficient by exclusion, as has occurred in many years.

Figure 1: Risk management efficiency

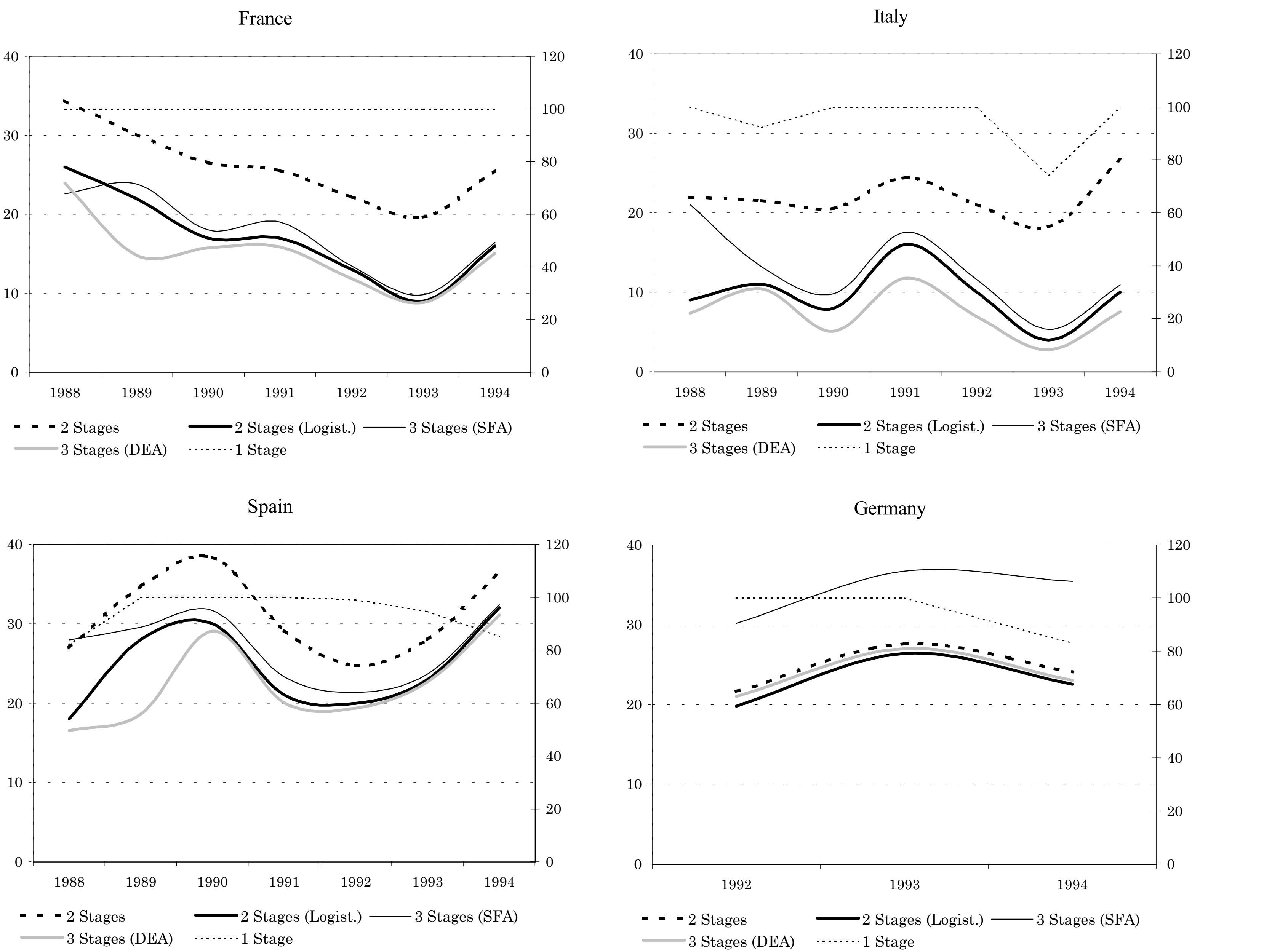


Table 2 : Percentage of bad loans (*PLL*) due to internal factors

	France					Italy				
	2 stages		3 stages		Average	2 stages		3 stages		Average
	Tobit	Logit	SFA	DEA		Tobit	Logit	SFA	DEA	
1988	65,6	74,0	77,4	76,0	**73,3**	78,0	91,0	78,9	92,7	**85,2**
1989	69,9	78,0	76,2	85,2	**77,3**	78,5	89,0	86,8	89,6	**86,0**
1990	73,5	83,0	82,0	84,3	**80,7**	79,5	92,0	90,2	94,9	**89,1**
1991	74,5	83,0	81,0	84,1	**80,7**	75,6	84,0	82,4	88,2	**82,5**
1992	77,8	87,0	86,6	88,2	**84,9**	78,9	90,0	88,4	93,1	**87,6**
1993	80,3	91,0	90,2	91,2	**88,2**	81,8	96,0	94,6	97,3	**92,4**
1994	74,5	84,0	83,6	85,0	**81,7**	73,4	90,0	89,1	92,5	**86,2**
Average	**73,7**	**82,9**	**82,4**	**84,9**	**81,0**	**78,0**	**90,3**	**87,2**	**92,6**	**87,0**

	Spain					Germany				
	2 stages		3 stages		Average	2 stages		3 stages		Average
	Tobit	Logit	SFA	DEA		Tobit	Logit	SFA	DEA	
1988	73,0	82,0	72,0	83,5	**77,6**	-	-	-	-	-
1989	65,3	72,0	70,4	81,4	**72,3**	-	-	-	-	-
1990	61,6	70,0	68,3	71,0	**67,7**	-	-	-	-	-
1991	70,8	79,0	76,7	80,0	**76,6**	-	-	-	-	-
1992	75,3	80,0	78,7	80,6	**78,6**	69,8	79,0	78,4	80,2	**76,9**
1993	72,0	77,0	76,3	77,3	**75,7**	63,3	73,0	72,4	73,6	**70,6**
1994	63,4	68,0	67,6	68,9	**67,0**	64,6	77,0	75,9	77,4	**73,7**
Average	**68,8**	**75,4**	**72,9**	**77,5**	**73,6**	**65,9**	**76,3**	**75,6**	**77,1**	**73,7**

5.2. Efficiency measures adjusted for risk (Phase 2) and adjusted for risk and environment (Phase 3)

The efficiency measures without adjusting for risk under VRS (ϑ) are presented in the column [1] of table 3. Their low value is indicative both of the highly heterogeneous character of the sample and of the existence of significant environmental differences. Referring, for the sake of simplicity, to the average of the results of all methods, Germany and France are the most efficient countries, while Italy is the least efficient, though this order differs according to the period considered. If we compare the results with those obtained in other studies, the result obtained for 1994 coincides totally with that obtained by Pastor, Lozano and Pastor (1997), and differs in points from that obtained by Pastor, Quesada and Pastor (1997) for the year 1992. The evolution of the efficiency of the Spanish banking sector, slightly decreasing, is very similar to that obtained by Pastor (1995a and 1996).

The efficiency measures adjusted for risk (ρ) are presented in table 3. Column [2] presents the results when all the bad loans is considered, mean while columns [3] to [6] present the results when only the proportion of bad loans due to internal factor is considered. Column [7] show the average of columns [3] to [6] which is also represented in figure 2. The order of countries changes substantially when credit risk is considered in the performance of banking firms. Now Spain and Germany are the most efficient countries, followed by France and Italy, indicating that the consideration of risk may be of vital importance when evaluating the efficiency and security of banking firms. Indeed, the inclusion of risk for these countries signifies on average an increase of efficiency of nearly 50%, or in other words the *risk management effect* (RME) is 0.53 and 0.56 respectively (see column [13]). Comparatively, this risk effect, or "prize" awarded to the Spanish banking sector for taking few risks, is higher in the period 1992-1994, during which the efficiency of risk management of Spanish banks improved notably.

The consideration of environmental variables does not, however, have such a marked effect on the measurements of efficiency (columns [8] to [12] in table 3 and figure 2). Thus, efficiency adjusted for risk and the environment (Ω) improves only slightly the position of those countries with a more unfavorable environment such as Italy, and to a lesser extent

Table 3: Efficiency measures adjusted for risk and environment.

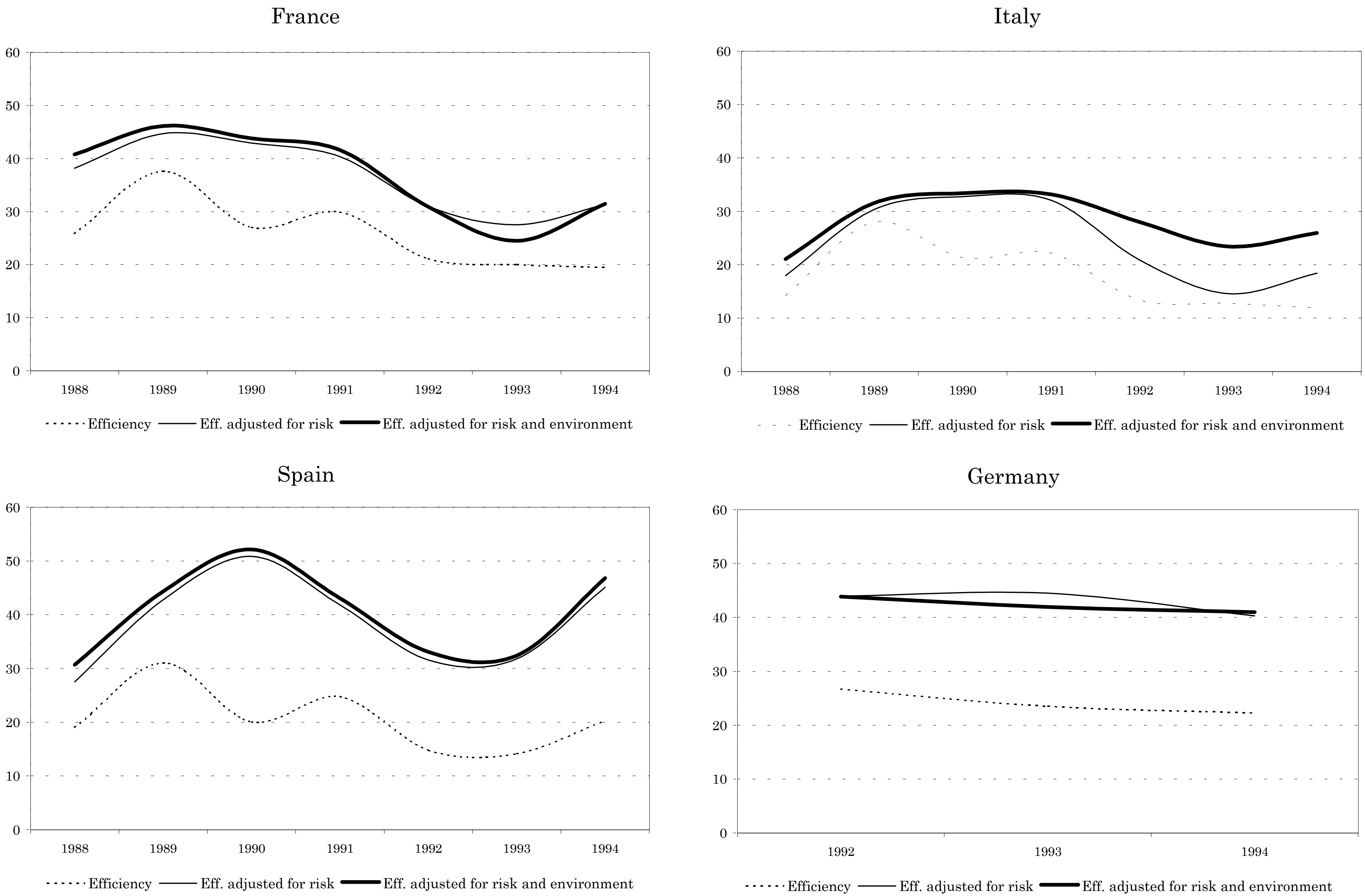
FRANCE														
			Eficiency adjusted for risk					**Eff. adjusted for risk and environment**						
			With PLL due to internal factors					*With PLL due to internal factors & env. vbles.*						
			2 stages		**3 stages**			**2 etapas**		**3 etapas**				
	Effic. VRS [1]	**With all *PLL* [2]**	**Tobit [3]**	**Logit [4]**	**SFA [5]**	**DEA [6]**	**Average [7]**	**Tobit [8]**	**Logit [9]**	**SFA [10]**	**DEA [11]**	**Average [12]**	**RME [13]= [1]/[7]**	**EE [14]= [7]/[12]**
1988	25,9	40,7	40,8	40,8	31,9	39,2	**38,2**	46,3	41,0	42,6	33,1	**40,8**	**0,68**	**0,94**
1989	37,6	37,6	45,6	44,7	44,2	44,2	**44,7**	47,9	45,0	47,4	44,2	**46,1**	**0,84**	**0,97**
1990	27,1	27,1	43,8	44,0	41,7	42,2	**42,9**	46,2	44,0	43,5	41,6	**43,8**	**0,63**	**0,98**
1991	30,0	30,0	41,8	41,8	38,4	39,4	**40,3**	45,1	42,0	40,9	38,4	**41,6**	**0,74**	**0,97**
1992	21,1	21,1	31,1	31,2	30,5	31,0	**30,9**	32,5	29,0	31,7	30,4	**30,9**	**0,68**	**1,00**
1993	20,0	20,0	26,7	26,9	28,1	28,3	**27,5**	28,5	24,0	23,0	22,5	**24,5**	**0,73**	**1,12**
1994	19,5	19,5	30,5	30,8	31,9	32,1	**31,3**	32,9	28,0	33,2	31,8	**31,5**	**0,62**	**0,99**
Average	**25,9**	**28,0**	**37,2**	**37,2**	**35,2**	**36,6**	**36,6**	**39,9**	**36,1**	**37,5**	**34,6**	**37,0**	**0,71**	**0,99**

ITALY														
			Eficiency adjusted for risk					**Eff. adjusted for risk and environment**						
			With PLL due to internal factors					*With PLL due to internal factors & env. vbles.*						
			2 stages		**3 stages**			**2 etapas**		**3 etapas**				
	Effic. VRS [1]	**With all *PLL* [2]**	**Tobit [3]**	**Logit [4]**	**SFA [5]**	**DEA [6]**	**Average [7]**	**Tobit [8]**	**Logit [9]**	**SFA [10]**	**DEA [11]**	**Average [12]**	**RME [13]= [1]/[7]**	**EE [14]= [7]/[12]**
1988	14,2	20,1	19,1	18,9	17,6	16,2	**17,9**	27,7	19,0	19,9	17,6	**21,1**	**0,79**	**0,85**
1989	28,0	32,8	31,9	31,8	28,3	29,4	**30,3**	35,1	32,0	30,9	28,3	**31,6**	**0,92**	**0,96**
1990	21,3	34,5	34,9	34,8	30,6	30,8	**32,8**	37,9	35,0	30,9	29,8	**33,4**	**0,65**	**0,98**
1991	22,2	35,9	35,9	35,9	27,5	28,9	**32,0**	38,6	36,0	30,6	27,5	**33,2**	**0,69**	**0,97**
1992	13,4	24,1	23,5	23,3	18,0	18,5	**20,8**	36,5	35,0	22,6	18,0	**28,0**	**0,64**	**0,74**
1993	12,8	17,2	15,2	15,1	13,9	14,2	**14,6**	32,7	31,0	16,0	14,0	**23,4**	**0,88**	**0,62**
1994	11,9	20,2	19,2	18,5	17,9	18,1	**18,4**	32,5	31,0	22,5	17,9	**26,0**	**0,64**	**0,71**
Average	**17,7**	**26,4**	**25,7**	**25,5**	**22,0**	**22,3**	**23,8**	**34,4**	**31,3**	**24,8**	**21,9**	**28,1**	**0,74**	**0,85**

SPAIN														
			Eficiency adjusted for risk					**Eff. adjusted for risk and environment**						
			With PLL due to internal factors					*With PLL due to internal factors & env. vbles.*						
			2 stages		**3 stages**			**2 etapas**		**3 etapas**				
	Effic. VRS [1]	**With all *PLL* [2]**	**Tobit [3]**	**Logit [4]**	**SFA [5]**	**DEA [6]**	**Average [7]**	**Tobit [8]**	**Logit [9]**	**SFA [10]**	**DEA [11]**	**Average [12]**	**RME [13]= [1]/[7]**	**EE [14]= [7]/[12]**
1988	19,0	29,2	28,8	27,5	26,4	27,4	**27,5**	35,8	27,0	33,4	26,6	**30,7**	**0,69**	**0,90**
1989	31,0	44,1	44,7	44,8	40,7	40,7	**42,8**	47,3	45,0	44,3	40,7	**44,3**	**0,73**	**0,96**
1990	20,1	51,1	53,9	54,0	47,5	47,9	**50,8**	57,2	54,0	49,9	47,4	**52,1**	**0,39**	**0,98**
1991	24,7	43,5	43,9	43,8	39,1	40,5	**41,8**	47,0	44,0	42,1	39,1	**43,1**	**0,59**	**0,97**
1992	14,8	32,7	31,1	33,1	30,6	31,4	**31,6**	35,7	34,0	32,2	30,5	**33,1**	**0,47**	**0,95**
1993	14,1	30,6	30,8	31,2	32,5	32,7	**31,8**	37,1	32,0	30,5	30,0	**32,4**	**0,45**	**0,98**
1994	20,3	45,3	45,4	45,6	44,7	44,9	**45,1**	50,8	46,0	45,7	44,7	**46,8**	**0,45**	**0,96**
Average	**20,6**	**39,5**	**39,8**	**40,0**	**37,4**	**37,9**	**38,8**	**44,4**	**40,3**	**39,7**	**37,0**	**40,4**	**0,53**	**0,96**

GERMANY														
			Eficiency adjusted for risk					**Eff. adjusted for risk and environment**						
			With PLL due to internal factors					*With PLL due to internal factors & env. vbles.*						
			2 stages		**3 stages**			**2 etapas**		**3 etapas**				
	Effic. VRS [1]	**With all *PLL* [2]**	**Tobit [3]**	**Logit [4]**	**SFA [5]**	**DEA [6]**	**Average [7]**	**Tobit [8]**	**Logit [9]**	**SFA [10]**	**DEA [11]**	**Average [12]**	**RME [13]= [1]/[7]**	**EE [14]= [7]/[12]**
1992	26,7	44,8	45,0	45,0	42,5	43,4	**44,0**	46,6	42,0	44,3	42,5	**43,8**	**0,61**	**1,00**
1993	23,5	39,4	44,8	44,8	44,1	44,3	**44,5**	47,5	42,0	39,5	38,8	**42,0**	**0,53**	**1,06**
1994	22,3	41,1	41,2	38,7	40,5	40,7	**40,3**	44,1	37,0	42,3	40,5	**41,0**	**0,55**	**0,98**
Average	**24,2**	**41,8**	**43,7**	**42,8**	**42,3**	**42,8**	**42,9**	**46,1**	**40,3**	**42,0**	**40,6**	**42,3**	**0,56**	**1,02**

Figure 2: Efficiency adjusted for risk and environment



Spain (with an environment effect of 0.83 and 0.96 respectively –see column [14]) whereas it penalizes banks belonging to banking systems with favorable environments such as Germany (with an *environmental effect* of 1.02 –see column [14]), indicating that part of its advantage in terms of efficiency is fictitiously originated by the environment. The average efficiency of the French banking system suffers no alteration (*environment effect* 0.99).

In general, unlike what happens in the case of efficiency in risk management, all countries underwent a reduction of efficiency from 1990, with an improvement in 1994. It is impossible to attribute the reduction of efficiency exclusively to Community de-regulation processes, but it is nonetheless true that this effect is expected in the short term in any de-regulatory process (Berg et al., 1992 and Humphrey 1993).

6. CONCLUSIONS

Existing literature on banking has paid little attention to the relationship between risk and efficiency. the few studies that attempt to obtain measurements of efficiency adjusted for risk are based on the inclusion of risk, measured through bad loan, as an additional input, implicitly assuming that all bad loan is due to firms' bad management and therefore excluding the possibility that part of it may be due to adverse economic circumstances. This procedure provides underestimated measurements of efficiency for those firms that have bad loans as a result of an adverse environment. Furthermore, none of these studies attempts to decompose bad loan into its internal and external components.

International comparisons of banking systems have traditionally found high degrees of inefficiency. This result is a consequence of constructing a common frontier without considering the influence of environmental variables.

In order to solve these problems in this study we propose a new three phase sequential procedure, based on the DEA technique, to identify and decompose the origin of bad loan and to obtain measurements of efficiency adjusted for risk and environment that are more refined than those hitherto proposed in other studies. In the first phase the procedure enables the total bad loan of each bank to be decomposed into its two components: one part due to bad risk management and another due to exogenous economic and environmental factors. For this we used several approaches for incorporating environmental variables into DEA, in order to test whether there were significant differences in the results. In the second phase, incorporating into the model only that part of bad loan that was due to bad management, measurements of efficiency adjusted for risk were obtained. Finally, in the third phase, by incorporating economic environment variables, we obtained efficiency indicators which, as well as being adjusted for risk, are adjusted for the economic environment.

The results obtained indicate that the technique proposed is not sensitive to the method of incorporation of environmental variables used. With the exception of the single stage method, all the methods give similar results. In general, efficiency in risk management improves in the case of the Spanish banking system, worsens in France, and remains stable in Italy and Germany. On average, the decomposition of bad loan into its internal and external components gives the result that about 80% of bad loan is due to factors internal to firms, while the rest is attributable to circumstances exogenous to firms.

Traditional measurements of efficiency, without adjustment for risk, are substantially different from those adjusted for risk. This feature is particularly important in those countries that are most efficient in risk management, such as Spain and Germany. In these cases, the "risk effect" or prize for being secure banking systems, is approximately 50%. The inclusion of environmental factors enabled efficiency to be corrected for the influence of environmental factors. In general, the results indicate that around 2% of the efficiency of the German banking system was fictitiously due to favorable economic circumstances (environment effect 1.02) whereas in other banking systems like those of Spain and Italy, subjected to unfavorable environments, efficiency was being under-estimated by 4% and 17% respectively (environment effect of 0.96 and 0.83 respectively).

APPENDIX

Three stage model

a) Stochastic frontier approach (SFA)

In this case the slacks - obtained in the first stage after solving problem (2) - are regressed against the environmental variables in a model that adopts the following specification:

$$[A.1] \quad \ln s_i = f(\ln Z_i; \beta) + v_i + u_i$$

where $f(\ln Z_i; \beta)$ is the deterministic frontier to be estimated with an error structure composed of a random term whose distribution is assumed to be normal, $v_i \sim N(0, \sigma_v^2)$ and a term $u_i \geq 0$.

The above expression is interpreted as the minimum slack that can be achieved in an environment with noise (v_i) and given the environmental variables. Any excess slack ($U_I>0$) is due to pure inefficiency, as correction has been made for environment.

Using the procedure of Jondrow et al. (1982) it is possible to separate the components of inefficiency (u_i) from noise (v_i). Operating on the above expression, Fried et al. (1996) obtain corrected slacks that represent the excess of the minimum slacks given the environment[22].

$$[A.2] \qquad s_i^* = s_i - \exp\{[f(\ln Z_i; \beta) + v_i]\} = \exp\{[f(\ln Z_i; \beta) + v_i]\} * [\exp(u_i) - 1] \geq 0$$

Fried et al. (1996) propose adding these corrected slacks (s_i^*) to the original inputs to obtain corrected inputs, in our case bad loan corrected for the influence of environment (PLL_i^*), by means of the following expression:

$$[A.3] \qquad PLL_i^* = PLL_i + \exp\{[f(\ln Z_i; \beta) + v_i]\} * [\exp(u_i) - 1] \geq PLL_i$$

These corrected inputs (PLL^*) are considered to cleanse bad loan of the effect of environmental variables, so that its use together with the original outputs in a DEA model in the third stage would provide the definitive indicators of "risk management efficiency" (γ_j).

[A.4]
$$\begin{aligned}
&Min_{\gamma,\lambda}\gamma_j\\
&\sum_{i=1}^{N}\lambda_i PLL_j^* \le \gamma_j PLL_j^*\\
&\sum_{i=1}^{N}\lambda_i L_i \ge L_j\\
&\sum_{i=1}^{N}\lambda_i = 1; \lambda_i \ge 0; \forall i
\end{aligned}$$

b) <u>DEA Model</u>

In this version, Fried et al. (1996) propose the inclusion of the sacks obtained in the first stage after solving problem (2) together with the environmental variables (Z_i) in the second stage using a DEA model[23].

[A.5]
$$\begin{aligned}
&Min_{\eta,\lambda} \quad \eta_j\\
&\sum_{i=1}^{N}\lambda_i s_i \le \eta_j s_j\\
&\sum_{i=1}^{N}\lambda_j Z_{pi}^+ \le Z_{pj}^+; \quad p = 1,..,P\\
&\sum_{i=1}^{N}\lambda_j Z_{qi}^- \ge Z_{qj}^-; \quad q = 1,...,Q\\
&\sum_{i=1}^{N}\lambda_i = 1; \lambda_i \ge 0; \quad \forall i
\end{aligned}$$

The interpretation of these efficiency indices (η_i), is the same as that of the efficiency indices (u_i) of the parametric stochastic version, so that following the same procedure, the inputs, in this case the PPDC, are corrected for the environment effect as follows:

[A.6]
$$PLL_i^* = PLL_i + \left(s_i - \sum_{i=1}^{N}\lambda_i s_i\right) \ge PLL_i$$

[22] Note that if $u_i=0$ then $s^*_i= s_i$,, which means that no adjustment would be made.
[23] Note that as in single stage models this procedure requires the imposition of the orientation of the influence of each environmental variable.

In those cases in which the firm is slack-efficient $(\eta_i = 1)$ no correction would be made, because $s_i - \sum_{i=1}^{N} \lambda_i s_i = 0$.

These corrected PLL* are used, together with the outputs (loans) in the third stage in a DEA model identical to (7) to obtain the definitive indicators of "efficiency in risk management" (γ_i).

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