BBR BRAZILIAN BUSINESS REVIEW
Vol. 5, No.1
Vitória-ES, Jan – Apr 2008
p. 18-34 *ISSN 1808-2386*

The Efficiency of Strategic Management in Brazil: the case of the banking system

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ABSTRACT: This article examines the efficiency of the 50 largest financial conglomerates in the Brazilian retail banking system by total volume of assets, among those with at least 50 branches in the country, based on figures from their published annual reports for 2004. After providing a brief historical background, we use data envelopment analysis (DEA) together with the I-O stepwise technique for variable selection. We introduce into the analysis the creation and simulation of artificial or unobserved productive units (artificial decision making units). At the end we analyze the financial institutions according to the results presented by the nonparametric DEA method, using the artificial DMUs, to observe the units considered as efficient and the variables that the inefficient units need to work on to improve their performance.

Key words: data envelopment analysis, artificial DMU, brazilian banking system, economics and finance.

Received in 09/14/2007; revised in 05/16/2008; accept in 05/26/2008.

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Editor's note: *This paper was accepted by Alexsandro Broedel Lopes.*

1. INTRODUCTION

The end of the last century was marked by intense competition in all sectors of the global economy. The more competitive a sector is, the stronger organizations have to be to survive. Thus the search for efficiency along with profitability is a constant task for managers. According to Ceretta and Niederauer (2000), the transformations in the international economy have been strongly affecting the Brazilian banking sector.

According to Marques, Matias and Camargo Junior (2004), a series of events and factors have been drastically changing the business climate for commercial banks around the world. Globalization, market opening and increased information technology investments are some of the most important factors that are creating a new scenario of competitive forces in these markets and imposing changes and concerns within banking organizations.

This work presents a comparison of the performance of the main financial conglomerates in the Brazilian banking sector, based on the data envelopment analysis technique, through management performance indicators.

The purpose of the proposed methodology is to characterize efficient and inefficient banks and to identify the variables that can be worked on to generate better results for those classified as inefficient by the model. In the analysis, we point out the financial institutions considered efficient, to serve as benchmarks, and those that are not efficient. By applying the model, it is possible to identify the optimal variables that need to be improved in inefficient companies to make them efficient. The sample of institutions analyzed consists of the main Brazilian banks, according to their annual reports filed with the Brazilian Central Bank for 2004.

2. THE BRAZILIAN BANKING SYSTEM

According to Carvalho (2005), the dominant type of financial institution in Brazil is the full-service bank, a type of institution that operates in various segments of the financial market, particularly in taking deposits, making and brokering loans and intermediating in bond market transactions.

The growing importance of public bond markets has stimulated the expansion of operting capacity in the bond markets. This has naturally prompted a trend for commercial banks to become universal banks, firmly engaged in the two main segments of the financial market: credit and papers.

For Marques, Matias and Camargo Junior (2004), banks play a crucial role in a country's economic development. They indirectly help the central bank in allocating the money supply, besides making the economy more dynamic. On the one hand they provide opportunities for small and medium savers to accumulate wealth over various horizons, and on the other they help individuals and companies that need to obtain loans.

Financial intermediation is the main function of the national banking system, with a fundamental role in adjusting the flow of savings to that of investments in the economy by harmonizing interests in function of time frames, volumes, yields and level of risk, which are not always similar between savers and borrowers, according to Silva (2000). Nevertheless, a bank, like any other productive unit, can and should be analyzed from a systemic perspective, to reveal its performance or productivity in using and allocating production factors.

According to Ceretta and Niederauer (2000), the Brazilian banking system has been undergoing a high level of mergers and acquisitions, becoming much more consolidated in recent years, aiming at greater solidity. Besides this, it is experiencing a rapid process of adaptation and expansion of modern management technologies to provide greater satisfaction to customers. This process is occurring both internally and externally, ranging from small operational adjustments to redefinition of the overall business strategy. These technologies seek to make banks more competitive through long-term efficiency gains and better profitability.

The 1988 Constitution sets important aspects of the Brazilian banking system. At the moment the entry of new foreign institutions is prohibited, except with authorization of the President. But between 1996 and 1998, various foreign banks received permission to establish a presence in the country through this provision, including by buying banks owned by state governments under the privatization program of those years. Foreign financial groups increased their share of total assets in the Brazilian banking sector from only 8.4% in 1993 to 22.9% in 2004. However, domestic banking groups still dominate the market. Today, among the nation's six largest banks, two are official (controlled by the federal government), three are under domestic private control and only one is foreign owned[1].

Another very important factor in the national financial market was the creation of PROER, a federal program under the auspices of the Central Bank to help the banking system weather the storm faced after monetary stability was achieved in 1994, after years of high inflation. Under this program, healthy banks were encouraged to take over sick ones, and the most distressed ones were taken over by the government itself for later sale of the healthy parts. Despite many criticisms, the program was unquestionably successful.

According to Carvalho (2005), the strength accumulated by banks during the inflationary period and the prompt action by the Central Bank to head off a crisis caused by the adjustment problems of weaker institutions to the new low-inflation environment, along with the efforts to modernize supervision through adhesion to the Basel I Accord, have resulted in a very sound and well capitalized banking system in Brazil, agile and efficient enough to take advantage of the opportunities offered by the market.

3. METHODOLOGY

The CCR model (Charnes, Cooper and Rhodes), growing out of data envelopment analysis (DEA) techniques, defines efficiency as the weighted sum of the outputs divided by the weighted sum of the inputs. This definition requires that a set of weights be attributed to all the decision making units (DMUs), which is a very complicated task. Charnes, Cooper and Rhodes (1978) presented a solution to this problem, arguing that each individual unit has a system of particular values and for this reason has legitimacy to define its own set of weights, seeking to maximize its efficiency. The only constraint imposed is that all the units have efficiency less than or equal to 1. Chart 1 shows the formulation of the CCR model for maximization of outputs and minimization of inputs.

Chart 1: CCR Model

<table>
<tr><th>Minimization of Inputs - CCR– I</th><th>Maximization of Outputs – CCR-O</th></tr>
<tr><td>

Primal (Multipliers)

$Max\ Eff_0 = \sum_{j=1}^{s} u_j y_{j0}$

Subject to:

$\sum_{i=1}^{r} v_i x_{ik} = 1$

$\sum_{j=1}^{s} u_j y_{jk} - \sum_{i=1}^{r} v_i x_{ik} \le 0, \quad K = 1,2,..n$

$u_j\ e\ v_i \ge 0\ \forall j,i$

Dual (Envelope)

$Min\theta$

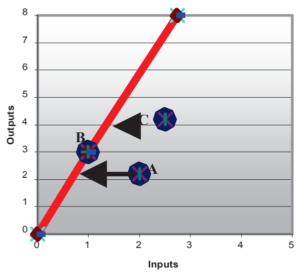
Subject to:

$\theta x_{i0} - \sum_{k=1}^{n} x_{ik} \lambda_k \ge 0, \quad i = 1,...,r$

$-y_{j0} + \sum_{k=1}^{n} y_{jk} \lambda_k \ge 0, \quad j = 1,..., s$

$\lambda_k \ge 0\ \forall\ k$

Graphical Representation



</td><td>

Primal (Multipliers)

$Min\ Eff_0 = \sum_{i=1}^{r} v_i x_{i0}$

Subject to:

$\sum_{i=1}^{r} u_j y_{jk} = 1$

$\sum_{i=1}^{r} v_i x_{ik} - \sum_{j=1}^{s} u_j y_{jk} \le 0, \quad K = 1,2,..n$

$u_j\ e\ v_i \ge 0\ \forall j,i$

Dual (Envelope)

$Max\ \theta$

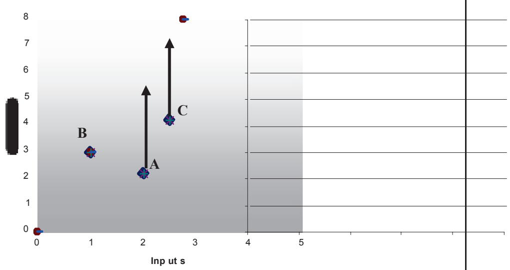
Subject to:

$\theta y_{j0} + \sum_{k=1}^{n} y_{jk} \lambda_k \ge 0, \quad i = 1,...,s$

$-x_{i0} + \sum_{k=1}^{n} x_{ik} \lambda_k \ge 0, j = 1,..., r$

$\lambda_k \ge 0\ \forall\ k$

Graphical Representation



</td></tr>
</table>

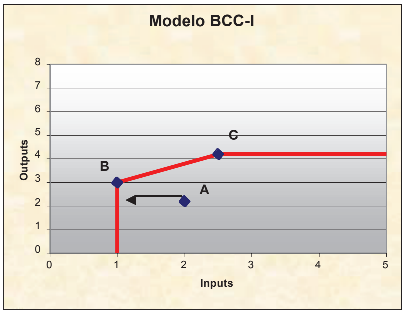
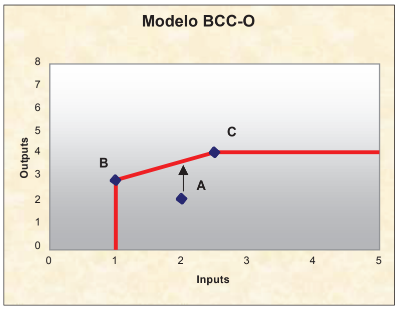
Where: Eff_0 – efficiency of DMU_0;
u_j , v_i – weights of the inputs and outputs, respectively;
x_{ik} , y_{jk} – inputs i and outputs j of DMU_K ;
x_{i0} , y_{j0} – inputs i and outputs j of DMU_K .

In the models' formulation it can be seen that the difference between the approaches is in the position of the variable λ_k in relation to the constraints. It is also possible to see that the production function, represented by the efficiency frontier, is strictly increasing, assuming that the production of the outputs can always grow, provided the inputs grow. For this reason, it can be concluded that the model has constant returns to scale (CRS).

The BCC model, developed by Banker, Charnes and Cooper (1984), arose as a form resulting from partitioning the efficiency of the CCR model into two components: technical efficiency and scale efficiency. The measure of technical efficiency resulting from the BCC model identifies the correct utilization of resources according to the operating scale of the

DMU. The scale efficiency is equal to the quotient of the BCC efficiency and the CCR efficiency. It gives a measure of the distance of each DMU being analyzed from an artificial DMU, which operates with the most productive scale efficiency. Chart 2 shows the model's formulations.

Chart 2: BCC Model

Minimization of Inputs - BCC– I	**Maximization of Outputs – BCC-O**
Primal (Envelope) $Min\ \theta$ Subject to: $\theta x_{i0} - \sum_{k=1}^{n} x_{ik}\lambda_k \ge 0$, i=1,2,..,r $-y_{j0} + \sum_{k=1}^{n} y_{jk}\lambda_k \ge 0$, j=1,2,..,s $\sum_{k=1}^{n}\lambda_k = 1$ $\lambda_k \ge 0\ \forall k$	Primal (Envelope) $Max\ \theta$ Subject to: $x_{i0} - \sum_{k=1}^{n} x_{ik}\lambda_k \ge 0$, i=1,2,..,r $-\theta y_{j0} + \sum_{k=1}^{n} y_{jk}\lambda_k \ge 0$, j=1,2,..,s $\sum_{k=1}^{n}\lambda_k = 1$ $\lambda_k \ge 0\ \forall k$
Dual (Multipliers) $Max\ Eff_0 = \sum_{j=1}^{s} u_j y_{j0} - u_*$ Subject to: $\sum_{i=1}^{r} v_i x_{ik} = 1$ $\sum_{j=1}^{s} u_j y_{jk} - \sum_{i=1}^{r} v_i x_{ik} - u_* \le 0, \quad K = 1,2,..n$ $u_j\ e\ v_i \ge 0\ \forall j, i$	Dual (Multipliers) $Min\ Eff_0 = \sum_{i=1}^{r} v_i x_{i0} - u_*$ Subject to: $\sum_{i=1}^{r} u_j y_{jk} = 1$ $\sum_{i=1}^{r} v_i x_{ik} - \sum_{j=1}^{s} u_j y_{jk} - u_* \le 0, \quad K = 1,2,..n$ $u_j\ e\ v_i \ge 0\ \forall j, i$
Graphical Representation 	Graphical Representation 

where: Eff_0 – efficiency of DMU_0;

u_j , v_i – weights of the outputs and inputs, respectively;

x_{ik} , y_{jk} – inputs i and outputs j of DMU_K ;

x_{i0} , y_{j0} – inputs i and outputs j of DMU_K .

Visually the difference between the formulations of the BCC and CCR models is the convexity constraint. However, the graphical representations also demonstrate that the models have some differences in the shape of the production function, determined by the convexity constraint, differentiating the objectives in the search for efficiency. In this work we use the

BCC model, oriented to minimize the inputs, due to the need to use output variables with negative values.

3.1 Limitations and advantages of DEA

According to Cooper, Seiford and Tone (2000), DEA, because it is a nonparametric evaluation method, has some characteristics that set it apart from other methods. In contrast to parametric methods, where the objective is to optimize a single regression plane, DEA individually optimizes each of the observations, one in relation to the others, to determine the efficiency frontier. Traditional parametric analysis applies the same production function to each of the observations. However, the focus of DEA is in the *n* optimizations, in contrast to the parameter estimations of the statistical approximations used by other methods.

Another advantage of DEA is that it does not require any functional form of the variables involved in the analyses. Besides this, it is also not necessary to make any assumption about the variables' distribution. The fact of being able to work with multiple outputs and inputs is an important advantage. Nevertheless, the variables present in the model must be chosen with great care, because the more variables there are, the weaker the model's discriminatory power will be.

In contrast to these advantages, there is a disadvantage related to the parameter estimation techniques. The hypotheses and the error related to estimating the frontier cannot be tested with statistical rigor, since the inputs and outputs can be random variables.

Based on the results obtained in previous works, it can be concluded that the model is efficient for the purpose here. We observe that it really is possible, through a comparative analysis, to find efficiency levels, and therefore to reach decisions more securely and efficiently.

3.2 DEA in evaluating the banking and financial sector

There are many studies in the international literature using DEA to analyze efficiency in the banking sector. Berger and Humphrey (1997) conducted a detailed review of 130 works, covering 21 countries, using efficient frontier analyses. There are also recent works, such as that of Yudistira (2002), that analyze the efficiency of Islamic banks. Nieto, Cinca and Molinero (2004) investigated the performance of microcredit institutions. Stavárek (2005) showed the efficiency of banks located in regions in different stages of integration with the European Union. Drake, Hall and Simper (2005) evaluated the efficiency of the Japanese banking sector. However, there are few studies of the Brazilian banking market.

Ceretta and Niederauder (2000) analyzed 144 Brazilian banking institutions based on their semiannual financial statements. They grouped these institutions into three categories, according to their size, measured by stockholders' equity, in order to make the groups more homogenous and to minimize any effects caused by size. They concluded that the largest institutions are the most efficient.

Another work that can be mentioned is Silva (2000). He examined the efficiency of the 25 largest Brazilian financial institutions, according to their total assets in March 2000. He used the DEA methodology together with the I-O stepwise method for variable selection. Of this group, 19 institutions were considered efficient.

The study of Gonçalves (2003) was very important, not only for the diffusion of the methodology to evaluate financial institutions, but also for the development of DEA as a tool that contemplates the opinion of specialists. He proposed a theorem to ensure equivalence between a set of constraints and the weights and the inclusion of an artificial DMU, and applied this to real data on a set of Brazilian investment funds.

Marques, Matias and Camargo Junior (2004) analyzed and compared 19 commercial and full-service banks in Brazil. The CCR and BCC models were developed for the 19 banks, considering cost factors as inputs and gains or profitability as outputs. The authors used a regression analysis to relate the scale inefficiency of the largest banks.

4. INITIAL ASPECTS OF THE ANALYSIS: DATABASE AND DESCRIPTION OF THE VARIABLES USED

4.1 Data gathering

The data for this study were obtained from the site of the Brazilian Central Bank, from the annual reports posted under the category "50 Largest Banks and Consolidated Data of the National Financial System."

4.2 Description of the variables

According to the opinion of specialists, we initially chose eleven variables to analyze the efficiency of the fifty largest Brazilian banks. Of these, six financial indexes represent input variables and five output variables. In choosing the variables we considered financial indexes of the "smaller the better" type to represent the input variables and those of the "bigger the better" type as the output variables.

Evaluation through the use of financial indexes helps analysts assess the financial health of organizations, shedding light on the strong and weak points related to their structure, liquidity, profitability and activity.

One of the main instruments to evaluate certain aspects of the past, present and future performance of firms, as explained by Perez Jr. and Begalli (1999), is to look at financial indexes, calculated basically from the financial statements. Financial analysis through indexes serves as a basis to judge performance and is considered by various authors as an eminently practical instrument.

4.2.1 Input variables

- Headcount: represents the total number of people directly employed by the financial institutions. It does not include outsourced workers [2].

- Number of Branches: represents all the branch banks serving the public, including "bank service posts" (branches within the installations or headquarters buildings of large companies, to serve employees).

- Leverage: indicates the ratio between third-party resources and own capital (debt and equity). This measures the institution's aggressiveness, and is obtained by dividing the total liabilities (less stockholders' equity) by stockholders' equity. The higher the index, the greater the risk involved in the institution's operations.

- Loan Default Rate: indicates the ratio between the provision for doubtful loans and the total amount of loans made. It is expressed as a percentage, representing the institution's nonperforming loan portfolio (loans subject to collection suits or of doubtful repayment). The lower this percentage is the better.

- Permanent Assets to Stockholders' Equity: indicates the proportion of equity invested in permanent assets (a category provided in Brazilian GAAP covering fixed assets, investments and deferred charges). The lower this ratio is the better, because there will be more resources available for working capital.

- Operating Overhead: indicates the institution's operational efficiency. Measured in points, it is obtained by dividing the sum of administrative and personnel expenses by the sum of the gross revenue from financial intermediation plus provision of services. It is a measure of the institution's efficiency, comparing its operating expenses with the main sources of revenue generated by those operations. The lower it is the better.

4.2.2 Output variables

- Result of Financial Intermediation: corresponds to the difference between revenues and expenses from financial intermediation (revenues from credit operations, funding expenses, results from securities operations, foreign exchange, compulsory reserves invested and others). This is taken from the amounts declared on the income statement.

- Return on Equity: measures the final return to shareholders on their equity. The higher it is the better. Expressed as a percentage, it is obtained by dividing the net income by the stockholders' equity, multiplied by 100.

- Operating Result: represents the gross revenues from financial intermediation and provision of services, the result of holdings in subsidiaries/affiliated companies and the balance of other revenues, divided by operating expenses less personnel and administrative expenses and taxes. This is taken from the income statement.

- Net Income: represents the final income for the year according to the legal rules, without considering the effects of inflation, after deducting the provision for income tax and social contribution and interest attributed to stockholders' equity (a way of paying dividends), considered as a financial expense. This is taken from the income statement, and the higher it is the better.

- Stockholders' Equity: indicates the institution's own resources, taken from the balance sheet. The higher it is the better.

4.3 Treatment of the Data

A difficulty faced in applying data envelopment analysis to financial statements is the impossibility of using negative values, because some of the most traditional accounting indicators can be negative. This is the case of net income, which can be positive (profit) or negative (loss). The measures of return on equity and on assets are also derived from the net income and thus can also assume negative values, as can the dynamic measures of the evolution of sales and financial indicators such as operating result. Some authors propose ways to overcome this limitation. If the number of units being evaluated is large, the possibility can be considered of simply discarding the units that have negative values under resources and products.

Another way of overcoming the problem of using negative values is based on the property of some DEA models, called translation invariance [Ali and Seiford (1990); Pastor (1997); Lovell and Pastor (1995)]. This property makes it so that the model's solution is not affected by a conversion (or transformation) of negative into positive values. Therefore, in some cases the efficiency scores are maintained and in others the classification into efficient and inefficient units is maintained.

The inclusion of negative variables in DEA was first dealt with in the article "Translation Invariance in Data Envelopment Analysis" by Ali and Seiford (1990). The Additive and BCC models were presented by them as enabling translating negative values into positive ones by adding a constant. They stress that for the second variable, the efficiency scores (i.e. the values of the objective function) for the inefficient DMU will be different when data are translated [Ali e Seiford (1990)].

Pastor (1997) presented an addition to the previous conclusions of Ali and Seiford (1990), proving that for the BCC Model, the property is limited: when the model is input oriented, the translation can only be applied to the outputs; and when it is output oriented, the transformation can only be applied to the inputs.

The strategy we followed to deal with the problem of negative variables was to use the model oriented toward minimization of inputs, as described by Kassai (2002), which deals with the application of DEA using financial indexes.

Based on the methods mentioned above, we made some modifications in specific variables. For the output variables that were negative, we created a constant composed of the most negative value of each variable plus one. We added this constant to the variables, which then became all positive. The variables modified by this process were: Result of Financial Intermediation, Return on Equity, Operating Result and Net Income.

We removed Banks 34, 41, 45 and 50 from the analysis because they had negative input variables, which would have made it impossible to apply the input minimization oriented methodology.

4.4 Variable selection method

The first procedure for choosing variables, according to the stepwise method, was carried out by Norman and Stoker (1991). This was followed by the work of Kittelsen (1993), who developed the theory behind the I-O stepwise method in a more applied form.

Norman and Stoker (1991) initiate the I-O stepwise method by defining an initial input-output pair. After this choice, the efficiency scores of the DMUs are calculated based on this pair. Besides this, the correlation coefficients of all the other variables are measured with the scores obtained. The list is then arranged in decreasing order of the absolute value of the correlation coefficient, and a causal analysis is used to select the next input variable, according to Lins and Meza (2000). The I-O stepwise method recognizes that there is prior information about the nature of the variable, that is, whether it is an input or output variable.

We selected our variables by the I-O stepwise method, as presented by Lins and Meza (2000). This method is based on the level of fit criterion, that is, the proximity to the efficient frontier. It is centered on comparison of the correlations between the variables and the efficiency, where an initial pair is chosen by observation of the highest correlation between the inputs and outputs. The initial pair can simply be chosen by the researcher based on his or her experience. The objective is to incorporate the parameter that permits the best fit of the DMU to the efficiency frontier.

Table 1: Inputs x Outputs Correlation Matrix

	Headcount	Number of Branches	Leverage	Loan Default Rate	Permanent Assets to Stockholders' Equity	Operating Overhead	Result of Financial Intermediation	Return on Equity	Operating Result	Net Income	Stockholders' Equity
Headcount	1.0000	0.9573	0.1982	0.2908	0.4465	-0.011	0.9235	0.2048	0.7253	0.7318	0.8123
Number of Branches	0.9573	1.0000	0.1267	0.2569	0.5062	-0.0221	0.9673	0.2245	0.8345	0.8391	0.9100
Leverage	0.1982	0.1267	1.0000	-0.1257	0.4283	-0.0798	0.0950	0.1052	0.0283	0.0163	-0.0246
Loan Default Rate	0.2908	0.2569	-0.1257	1.0000	0.1749	0.2430	0.2728	0.0809	0.1869	0.1985	0.1828
Permanent Assets to Stockholders' Equity	0.4465	0.5062	0.4283	0.1749	1.0000	0.1510	0.5063	0.1603	0.4281	0.4829	0.4960
Operating Overhead	-0.0111	-0.0221	-0.0798	0.2430	0.151	1.0000	-0.0843	-0.5746	-0.1474	-0.1484	-0.0566
Result of Financial Intermediation	0.9235	0.9673	0.095	0.2728	0.5063	-0.0843	1.0000	0.2831	0.8961	0.9199	0.9493
Return on Equity	0.2048	0.2245	0.1052	0.0809	0.1603	-0.5746	0.2831	1.0000	0.3328	0.9199	0.9493
Operating Result	0.7253	0.8345	0.0283	0.1869	0.4281	-0.1474	0.8961	0.3328	1.0000	0.9736	0.8796
Net Income	0.7318	0.8391	0.0163	0.1985	0.4829	-0.1484	0.9199	0.3485	0.9736	1.0000	0.9055
Stockholders' Equity	0.8123	0.9100	-0.0246	0.1828	0.4960	-0.0566	0.9493	0.1874	0.8796	0.9055	1.0000

Based on the results of the correlation matrix shown above, we decided to eliminate the *number of branches"* variable, because it is highly correlated with *headcount* variable. According to specialists, the latter is logically more important to measure a bank's scale. Among the outputs, we removed *stockholders' equity* and *net income*. We did this for two reasons: both are highly correlated with other outputs (*result of financial intermediation* and *operating result,* respectively). Besides this, these variables are already included in *profitability,* with the advantage that this is not sensitive to the bank's scale.

Based on the correlations, the initial pair chosen was *result of financial intermediation* and *headcount*. After choosing this pair, we ran the model, generating an efficiency vector. Then the input of the next variable is obtained by comparing the correlations between the variables and the efficiency vector, that is, the variable with the highest correlation with the efficiency enters the model. The results of this step can be seen in Table 2.

Table 2: Correlation Matrix of the Variables with the Efficiency Vectors

	MODIN	MOD2	MOD3	MOD4
Leverage	-0.0,25	-0.013	**0.016**	-
Loan Default Rate	-0.042	**0.091**	-	-
Permanent Assets to Stockholders' Equity	**-0.125**	-	-	-
Operating Overhead	-0.331	-0.325	0.241	-0.241
Return on Equity	0.208	0.231	0.165	0.226
Operating Result	0.613	0.636	0.596	0.537

It can be seen above that the *permanent assets to stockholders' equity*, *loan default rate* and *leverage* variables, respectively, have been introduced into the model. Although the *return on equity* variable was not chosen for the model by the I-O stepwise method, we believed this variable would be extremely important to evaluate bank efficiency, since it can be considered an efficiency indicator by itself. As in DEA models, the inclusion of a new variable can cause reduced efficiency of any unit. The variables that do not alter the efficiency scores significantly are thus identified as factors that do not help the DMU to approach the efficiency frontier. Therefore, these criteria are discarded from the model. Below, the mean efficiency of the model can be seen after the inclusion of each of the variables.

Table 3: Iterations / Mean Efficiency / MOD4 + Profitability

Iterations	Mean Efficiency
MODIN	21.26
MOD2	24.24
MOD3	28.96
MDO4	35.53
MOD4+Profitability	50.23

The process of entering new variables ends when the researcher thinks it will not cause any significant change in efficiency, or when only variables are left that have undesired correlation with efficiency. The proposed model works with variables characterized as financial indicators, which makes it more discriminatory. This fact means the model's average efficiency is lower than usually observed when working with variables that express quantities.

4.5 Universe analyzed

We excluded from the analysis banks that focus their business in the wholesale sector, mainly engaging in structured operations with large companies, as well as those mainly involved in making personal loans. We believe these financial institutions do not have the same characteristics and objectives as large retail or full service banks with at least 50 branches. After eliminating the institutions focused on niche markets, there were 21 institutions remaining, representing approximately 75% of the entire national financial system in terms of assets.

5. Artificial DMUs: introducing the specialist's opinion

According to Figueiredo (2005), the flexibility in choosing the weights in the classic DEA methodology is important in identifying inefficient DMUs, that is, those with low performance even with weights defined more favorably. Nevertheless, the attribution of weights in DEA is no easy task. The choice of the weights introduced in the PPL through the constraints can make it impossible to obtain a solution.

Roll and Golany (1991) stated that each weight in DEA, strictly positive, is equivalent to an unobserved DMU (artificial DMU), introduced among the others at the time of analysis. Allen et al. (1997) generalized this observation for the case of multiple inputs and/or outputs, for DMUs that operate with constant or variable scale returns. Therefore, the inclusion of an artificial DMU in the original set of DMUs acts as an alternate method to simulate a set of weight constraints, with the efficiency indexes of this new set calculated by the classic method, without weight restrictions, the same as is obtained with the initial set of DMUs utilizing weight constraints instead of artificial DMUs. The coordinates chosen for the artificial DMUs are fundamental to find a solution effectively.

As observed in Gonçalves (2003), in the CCR model the artificial DMUs can be defined using equations (4.1) or (4.2), without any difference in the results. Both simulate the ARI and ARII restrictions.

$$y_{rjt} = \frac{y_{rj}}{h_j^*} \quad \text{e} \quad x_{ijt} = x_{iij} \quad \forall jt = j \qquad (4.1)$$

$$y_{rjt} = y_{rj} \quad \text{e} \quad x_{ijt} = x_{iij} \times h_j^* \quad \forall jt = j \qquad (4.2)$$

In contrast, for the BBC model the efficiency depends on the model's orientation. Thus, the definition of the artificial DMU using contraction of the inputs according to equations (4.3) does not produce the same results if the expansion of the outputs is used, according to equations (4.4).

$$y_{rjv} = y_{rj} \quad \text{and} \quad x_{ijv} = x_{ij} \times v_i^* \quad \forall jv = j \qquad (4.3)$$

$$y_{rjv} = \frac{y_{rj}}{v_j^*} \quad \text{and} \quad x_{ijv} = x_{ij} \quad \forall jv = j \qquad (4.4)$$

Figueiredo (2005) made a generalization of the restrictions of Gonçalves (2003) for multidimensional problems.

In the case here, we established the mean profitability as the cut-off point, that is, no bank with below average profitability could be more efficient than another with above average profitability. Therefore, in this case we introduced an artificial DMU and it took five iterations to obtain the final results. The definition of the cut-off was fundamental to apply the constraints of Gonçalves (2003), because without this definition it would have been impossible to apply the methodology.

6. ANALYSIS OF THE RESULTS

Table 4 below shows the final results of the DEA BCC model oriented to minimizing the inputs, considering the variables selected by the I-O stepwise method and with the artificial DMUs inserted.

Table 4: Bank / Profitability / Class / Above Average / Below Average

Bank	Profitability	Class	Score	Bank	Profitability	Class	Score
ARTIFIC1	18.38	-	100	Bank 48	28.80	Above Average	83.77
ARTIFIC2	22.73	-	100	Bank 38	30.03	Above Average	78.97
ARTIFIC3	11.03	-	100	Bank 22	32.13	Above Average	75.96
ARTIFIC4	21.77	-	100	Bank 6	32.58	Above Average	64.17
ARTIFIC5	24.96	-	100	Bank 32	32.59	Above Average	56.88
Bank8	38.77	Above Average	100	Bank 21	25.50	Below Average	56.69
Bank10	31.55	Above Average	100	Bank 9	22.73	Below Average	56.25
Bank13	32.33	Above Average	100	Bank 7	18.38	Below Average	56.03
Bank35	39.41	Above Average	100	Bank 2	21.77	Below Average	56.02
Bank42	30.82	Above Average	100	Bank 23	11.03	Below Average	56.01
Bank43	29.89	Above Average	100	Bank 18	24.96	Below Average	55.97
Bank44	29.91	Above Average	100	Bank 37	25.22	Below Average	55.08
Bank20	33.16	Above Average	98.00	Bank 14	28.14	Below Average	42.20

We considered one-third of the 21 banks to be efficient. In 2004, retail banks had a banner year, one of the best in recent years. With the economy growing (albeit less than hoped) and with high interest rates and spreads, banks considered efficient directed their activities toward credit operations. Table 5 shows the weights space of the banks considered efficient, classified as: High Contribution (HC), Medium Contribution (MC), Low Contribution (LC) and No Contribution (NC).

Table 5: Weights Attributed by the DEA-BCC Model – Efficient Banks

Banks	Artific 1	Artific 2	Artific 3	Artific 4	Artific 5	Bank 8	Bank 10	Bank 13	Bank 36	Bank 42	Bank 43	Bank 44
Headcount	AC	NC	MC	BC	BC	AC	NC	NC	AC	AC	AC	NC
Leverage	NC	AC	MC	NC	NC	NC	NC	NC	NC	NC	NC	NC
Loan Default Rate	NC	NC	NC	AC	NC	NC	NC	NC	BC	NC	NC	AC
Permanent Assets to Stockholders' Equity	NC	NC	NC	NC	AC	NC	AC	AC	NC	NC	NC	NC
Result of Financial Intermediation	AC	NC	NC	AC	BC	NC	AC	NC	AC	AC	AC	BC
Return on Equity	BC	AC	NC	NC	NC	AC	NC	BC	BC	AC	MC	AC

All the DMUs have at least one variable with zero weight (NC) attributed. This means that the variable was disregarded in calculating the DMU's efficiency, probably because if it had been considered, the bank (DMU) could not have been any more efficient. Or it could simply be because the solution found by the model was not the one that considers weights other than zero for all the variables. That solution may exist and this will make the DMU to be considered as efficient.

In Table 5 it can also be seen that the *return on equity, result of financial intermediation* and *headcount* were the most representative ones in calculating the score of the efficient banks.

Regarding this efficiency, the expansion of credit, spurred particularly by personal loans with repayment by automatic deductions from payroll or retirement benefits (previously only legally allowed for civil servants) was one of the main factors responsible for the increased revenues of financial institutions. Bank 35, for example, increased its loan portfolio by 31% and its revenue from operations grew 35%. This reflects directly on the *return on equity* and *result of financial intermediation* variables, which were amply considered by the model in calculating this bank's efficiency.

Another strategy used by banks considered efficient in the sample was the creation of specific departments with increasing freedom to act independently, in the following segments: wholesale, middle market and personal loans.

Although they declined because of the expansion of credit discussed above, treasury operations, mainly with government bonds, still provided good returns for these financial institutions, as can be seen in the *result of financial intermediation* variable.

Besides this, the acquisition of smaller banks and joint ventures with other companies also should be taken into consideration as factors helping to increase the profits of the banks considered efficient. Bank 35, for example, joined with Bank 17 and a large supermarket chain to expand its presence in the lending segment, with high spreads, basically aimed at lower income consumers. This allowed it to spread its bad loan risk, with a direct effect on the *default rate* and *return on equity* variables, which were amply considered in calculating its efficiency.

Another interesting observation regarding the banks deemed efficient can be made about Bank 10, which for many years worked only with the public sector, offering loans with payroll deduction repayments at high spreads and low risk. That fact directly affected the *result of financial intermediation* variable, amply considered in calculating its efficiency. Another interesting fact is this bank's low permanent assets to equity ratio.

Below are the results of the inputs decreases necessary for each bank to reach the efficiency frontier.

Table 6: Decrease of Inputs to Reach the Efficiency Frontier

	Bank 2	Bank 6	Bank 9	Bank 14	Bank 18	Bank 20	Bank 21	Bank 22	Bank 32	Bank 37	Bank 38	Bank 37	Bank 48
Headcount	-43.98	-35.83	-44.00	-57.80	-44.03	-13.91	-43.31	-24.04	-44.99	-43.12	-50.66	-21.03	-16.23
Leverage	-44.03	-74.49	-43.75	-76.92	-44.09	-2.00	-48.06	-42.24	-44.06	-55.43	-57.86	-68.38	-18.12
Loan Default Rate	-43.98	-35.83	-43.93	-57.80	-44.16	-2.00	-48.25	-50.99	-44.06	-43.12	-44.92	-56.88	-21.14
Permanent Assets to Stockholders' Equity	-43.98	-84.69	-44.00	-87.94	-44.03	-12.87	-67.40	-24.04	-44.02	-54.12	-79.20	-21.03	-38.71

A specific analysis of each variable shows that regarding headcount, Bank 14 needs to downsize substantially, while Bank 20 and Bank 48 need to make smaller staffing cuts. The bank with the worst leverage situation is Bank 6, which needs reductions of roughly 75% to reach the frontier. In contrast, Bank 20 only needs to reduce this variable by 2%. Bank 14 is the one that needs to make the most improvements in its loan default rate, while Bank 20 needs the smallest adjustments in this respect. The reductions related to the ratio of permanent assets to stockholders' equity need to be stronger in Bank 6, while Bank 20 only needs to reduce this variable by 12%.

Overall, Bank 20 and Bank 48 need the smallest decreases in the variables to become efficient, while Bank 14 and Bank 6 need the most radical changes.

Table 7: Weights Attributed by the DEA-BCC Model – Inefficient Banks

Banks	Bank 2	Bank 6	Bank 7	Bank 9	Bank 14	Bank 18	Bank 20	Bank 21	Bank 22	Bank 23	Bank 32	Bank 37	Bank 38	Bank 40
Headcount	BN	BC	MC	NC	MC	BC	NC	AC	MC	AC	AC	AC	BC	AC
Leverage	NC	NC	BC	AC	NC	NC	BC	NC	NC	NC	NC	NC	NC	NC
Loan Default Rate	NC	BC	NC	NC	BC	NC	AC	NC	NC	NC	BC	AC	NC	NC
Permanent Assets to Stockholders' Equity	AC	NC	BC	NC	NC	AC	NC	NC	BC	NC	NC	NC	MC	NC
Result of Financial Intermediation	AC	NC	AC	NC	NC	BC	AC	BC	AC	NC	AC	NC	AC	AC
Return on Equity	NC	AC	AC	AC	BC	BC	NC	BC	BC	BC	AC	AC	AC	BC

The same comments made about Table 5 apply to Table 7 as well, namely that the variable with zero weight was disregarded in calculating the DMU efficiency, probably because if it had been considered, the bank (DMU) could have been even more inefficient. For inefficient banks, the *return on equity, result of financial intermediation* and *headcount* variables also were the most representative ones in calculating the score, as was the case for the efficient banks. These are classified in Table 7 as: High Contribution (HC), Medium Contribution (MC), Low Contribution (LC) and No Contribution (NC).

7. CONCLUSIONS AND RECOMMENDATIONS

One of the main advantages of the DEA methodology can be seen from this study: the identification and definition of the efficient units as a benchmark for the others. This is an effective management analysis tool, because besides indicating problem areas, it suggests the path to attain efficiency.

The choice of financial indicators as variables strengthened the model in the sense of covering in discriminatory form aspects involving the capital structure, financial cycle and operational results of the financial institutions.

The application of the artificial DMUs instead of the weights constraints technique for the cases of multiple inputs and/or outputs showed that no unit with undesirable output can have a better efficiency index than any unit with acceptable output. It also proved feasible in the case analyzed, because it aggregated the opinion of specialists and reached the same conclusions in a simpler way.

Two-thirds of the institutions were not considered efficient. In examining their histories, we can cite as main inefficiency factors the fact that some institutions showed problems in lending operations, reflecting negatively on their results, besides the fact that some financial conglomerates were passing through mergers that were not yet finalized, thus causing structural problems.

Another inefficiency factor is the delay of some institutions in keeping up with the frequent changes in the market, such as variations in interest rates, and the tendency to associate with companies in other sectors in an attempt to expand their loan portfolios along with other banking products and services to new customers.

As recommendations for future research, we suggest extending this type of study to longer time intervals. Also, future studies could utilize other variables, such as exogenous factors to banks, i.e., variations in the reference interest rate, exchange rate and/or domestic and foreign stock market indexes that influence domestic investing activity. Future works could also compare the Brazilian financial market with those of other countries, focusing on international financial conglomerates.

Another question bearing further study is the model's orientation in contexts where there are negative variables, because in the case studied here, the input orientation made this imperative. New techniques to enable solutions to this problem would be welcome.

Based on the results obtained, we can say that the model is efficient for the intended purpose, and that the results confirm that it is possible, through a comparative analysis, to indicate the efficiency levels to facilitate faster and more secure management decisions.

Notes

[1] Brazilian Central Bank (2006) <www.bcb.gov.br>.

[2] Numbers declared by financial institutions at the site of the Brazilian Central Bank <www.bcb.gov.br>.

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