Production, 26(3), 551-561, jul./set. 2016
http://dx.doi.org/10.1590/0103-6513.185714

Estimating the efficiency from Brazilian banks: a bootstrapped Data Envelopment Analysis (DEA)

Ana Elisa Périco[a*], Naja Brandão Santana[b], Daisy Aparecida do Nascimento Rebelatto[c]
[a]Departamento de Economia, Faculdade de Ciências e Letras, Universidade Estadual Paulista, Araraquara, SP, Brasil
[b]Centro de Ciências da Natureza, Universidade Federal de São Carlos, Buri, SP, Brasil
[c]Departamento de Engenharia de Produção, Escola de Engenharia de São Carlos, Universidade de São Paulo, São Carlos, SP, Brasil
*anaelisa@fclar.unesp.br

Abstract

The Brazilian banking sector went through several changes in its structure over the past few years. Such changes are related to fusions and acquisitions, as well as the largest market opening to foreign banks. The objective of this paper is to analyze, by applying the bootstrap DEA, the efficiency of banks in Brazil in 2010-2013. The methodology was applied to 30 largest banking organizations in a financial intermediation approach. In that model, the resources entering a bank in the form of deposits and total assets are classified as inputs and besides these manual labor is also considered as a resource capable of generating results. For the output variable, credit operations represent the most appropriate alternative, considering the role of the bank as a financial intermediary. In this work, the matter of the best classification among retail banks and banks specialized in credit has little relevance. The low relevance in this type of comparison is a result of analysis by segments (segments were analyzed separately). The results presented here point to an average level of efficiency for the large Brazilian banks in the period. This scenario requires efforts to reduce expenses but also to increase revenues.

Keywords

Bank efficiency. Data Envelopment Analysis (DEA). Financial intermediation. Bootstrap.

1. Introduction

The Brazilian banking sector has experienced vast changes over the last years. This provoked a wave of banking mergers and acquisitions (M&As) and the penetration of some foreign banks into the Brazilian retail banking market. Such processes focus on providing the institutions greater power in this competitive environment. Coupled to this, there are numerous innovative processes related to management, which also allow banks to not only further improve customer service, but also to offer a greater variety of services at lower costs.

The objective of this paper is to analyze, by applying the bootstrap DEA, the efficiency of banks in Brazil, using a financial intermediation. To reach the proposed goal, we use the database entitled "The Largest Banks", from 2010 to 2013, which is periodically published by the Central Bank of Brazil.

The banking literature recognizes the vast progress made by banks with regard to its main functions and responsibilities. Over time, practically everywhere in the world, the changes seen in the banks' function are remarkable, with new products and services increasingly available to customers. However, the financial intermediary role still prevails. In fact, all the other features incorporated into the functions of a bank are still the result of its primary function, which is financial intermediation.

The structure of the paper is as follows: Section two presents a brief literature review on bank efficiency. Section three describes the data, the employed methodology and the proposed DEA-based. Section four discusses the results obtained from the application of the model, and the final remarks are in section five.

Received: Oct. 23, 2014; Accepted: Nov. 12, 2015

2. Efficiency studies of the banking systems

The literature offers two main approaches to evaluate the efficiency of banks: financial intermediation and results. The intermediation approach (Sealey & Lindley, 1977) originates directly from the traditional role of financial institutions as financial intermediaries, in which the bank's main activity is related to raising funds from savings and redirecting it to borrowers (deficit agents). Thus, in that model the resources entering a bank in the form of deposits and capital are classified as inputs and besides these manual labor is also considered as a resource capable of generating results. For the output variable, credit operations represent the most appropriate alternative, considering the role of the bank as a financial intermediary.

For the result-oriented approach, a set of expenditures is considered on the input side, and a set of revenues on the output side (Giokas, 2008).

This work regards the recent literature that investigates the characteristics of banks, influences on credit, as well as factors related to the performance of these institutions.

On the subject of banking efficiency, Halkos & Tzeremes (2013) analyzed the efficiency of forty-five Greek banks that participated in merger or acquisition processes. The results showed that in periods of crisis, most of these banks were unable to generate operational efficiency gains – yet in less turbulent periods, the efficiency gains were observed. Halkos & Salamouris (2004) analyzed the Greek commercial banks with the use of financial ratios. They find a wide variation in performance and show that the increase in efficiency was accompanied of a reduction in the number of small banks due to mergers and acquisitions. Several authors have investigated banking efficiency taking into consideration different aspects. Paradi et al. (2011), for example, argue that the management related aspects are crucial in determining the efficiency of a bank. However, by contrast, much of the work conducted on bank efficiency (Gaganis et al., 2009; Giokas, 2008; Portela & Thanassoulis, 2007; Pastor et al., 2006; Stavarek, 2005; among others) does not even consider using management variables to measure efficiency.

Gaganis et al. (2009), considering the variables used to measure efficiency and the results found, point to risk (non-payment) as the main element to determine the effectiveness of the Greek banks analyzed. The results of Pastor et al. (2006) for European banks are in line with the results of Gaganis et al. (2009).

Determining efficiency will depend greatly on the variables used and the efficiency approach chosen. Some authors claim that the size of the bank is a determining factor for its efficiency, as for instance, in Macedo & Barbosa (2009), which clearly defends the middle-market segment. These authors observed a relationship between bank size and performance, since the results show that in this segment it is not possible for a small institution to have high performance. Périco et al. (2008) claim that the size of a bank was not a decisive factor to attribute efficiency, given that in Brazil many medium and small banks had greater efficiency than the bigger banks.

The literature contains a wide range of models within different efficiency approaches, always striving for greater performance by the decision makers. Ultimately, the driving force of this work is to contribute to this discussion.

3. Data and methodology

This section is divided into three parts. The first part is a summary of main information concerning the data used in this research: the composition of the investigated sample, specification of variables used, temporal delimitation, as well as the data source. The second and third parts represent brief descriptions and characterization of the techniques used in the manipulation of data: Data Envelopment Analysis and the technique of Bootstrap resampling.

3.1. Data

In this study we used a sample of the 30 largest banks, in accordance with the classification criteria used by the Central Bank for all periods. It should be noted that only Commercial Bank institutions or Multiple Banks with commercial portfolios were selected.

We sought to work with institutions of all sizes (large, medium and small) and service sectors (retail and loan specialized – specific niches) to enable the analysis to also consider these aspects.

In our analysis, we use the intermediation approach, considering that financial institutions act as intermediates between depositors and borrowers. Therefore, we define our DEA formulation based on the adaptation of several other studies (Sealey & Lindley, 1977; Berger & Humphrey, 1992, 1997; Drake & Hall, 2003; Fukuyama & Matousek, 2011) by using total deposits, labor and total assets as inputs, and credit operations as output.

It is worth noting that the selection of these variables followed mainly two parameters. The first one is related to the variables used in similar studies developed in other countries. Sealey & Lindley (1977), as Berger & Humphrey (1992, 1997), are important references of international banking literature, the first studies on bank efficiency were carried out by them. The other authors followed a similar pattern.

The second parameter which justifies the use of these variables is related to the recognition of the fundamental role of a bank: financial intermediation. The bank raises funds (deposits) to generate credit operations. To capture the deposits are required employees and fixed investments (total assets). Table 1 presents details about the variables.

The data used were the banking institutions' annual financial records from January 2010 to December 2013, obtained from the website of the Central Bank of Brazil, in the report "Top 50 Banks" (see Table 2 for the descriptive statistics of the variables used).

3.2. Data Envelopment Analysis

DEA is an operational research technique, which is based on linear programming with the objective to comparatively analyze independent units in terms of their relative performance. As it does not use a pre-defined production function, identical to all organizations in the input-output relationship analysis, it is classified as non-parametric. Therefore, the data envelopment analysis not require preparing a fixed weighted formula to measure the efficiency of the units under analysis, because the weights of each variable are determined by the technique itself.

DEA can be regarded as a body of concepts and methodologies incorporated into a collection of models with different possible interpretations (Charnes et al., 1994). The envelopment surface will differ depending on the scale assumptions that underpin the model. Two scale assumptions are generally employed: constant returns to scale (CRS) and variable returns to scale (VRS). CRS reflects the fact that output will change in the same proportion as inputs are changed; VRS reflects the fact that production technology may exhibit increasing, constant and decreasing returns to scale.

The output-oriented model with variable returns to scale (Banker et al., 1984) is given below (Equation 1):

Table 1. The Description of variables.

Variable	Description	Type of variable
Deposits	Total funds raised by the bank (R$)	Input
Total Assets	The sum of current and long-term investment owned by a bank (R$)	Input
Employees	Number of bank employees	Input
Credit Operations	Credit operations granted by the bank (R$)	Output

Table 2. Descriptive statistics of the inputs and output.

Year	2010	2011	2012	2013
Deposits				
Mean	45,662,815.0333	52,111,521.9000	54,225,431.2000	55,890,598.0333
Median	6,195,700.5000	7,739,967.5000	8,037,936.5000	8,234,600.0000
Std	89,440,803.7244	104,438,742.1259	112,133,179.0300	115,960,689.4802
Min	432,834.0000	895,983.0000	1,344,640.0000	556,611.0000
Max	377,446,483.0000	442,770,913.0000	472,872,818.0000	471,243,653.0000
Total Assets				
Mean	10,132,400.5667	11,480,704.7333	13,125,997.2000	13,107,163.9000
Median	2,066,865.5000	2,371,074.5000	2,744,227.0000	2,750,188.5000
Std	18,941,726.7802	21,136,195.8139	23,894,829.0176	23,752,629.3726
Min	202,639.0000	402,139.0000	463,681.0000	573,968.0000
Max	65,322,455.0000	72,528,414.0000	82,825,221.0000	86,466,898.0000
Employees				
Mean	19,584.1000	20,411.1667	20,448.4667	20,255.2667
Median	1,393.5000	1,448.5000	1,438.5000	1,447.5000
Std	38,268.5442	39,736.4027	40,236.3999	39,881.8453
Min	42.0000	39.0000	35.0000	15.0000
Max	126,426.0000	131,299.0000	130,638.0000	125,319.0000
Credit Operations				
Mean	44,431,701.5000	54,471,156.1333	63,924,616.0667	71,502,946.9333
Median	6,543,292.5000	7,212,109.0000	8,438,871.5000	9,705,813.0000
Std	83,740,418.2047	103,283,982.5529	124,735,576.2180	142,795,921.3199
Min	145,318.0000	187,137.0000	467,251.0000	639,309.0000
Max	334,193,046.0000	397,521,161.0000	490,532,302.0000	547,948,114.0000

$$
\begin{aligned}
&\text{Min } \hat{\theta}_{DEA} = \sum_{i=1}^{n} v_i x_{ki} + v_k \\
&\textit{Subjetct to}: \\
&\sum_{r=1}^{m} u_r y_{rk} = 1 \\
&-\sum_{i=1}^{n} v_i x_{jr} + \sum_{r=1}^{m} u_r y_{jr} - v_k \leq 0 \\
&u_r, v_i \geq 0
\end{aligned}
\tag{1}
$$

where: y = output; x = inputs; u, v = weights; r = 1,..., m.; i = 1,..., n; j=1,...,n.

The variables u_k and v_k are introduced, representing the variable returns to scale. These variables should not meet the constraint of positivity and may be negative values.

Among the DEA models, it is possible (and recommended) to choose the most suitable one for the sample, through the testing hypotheses of returns to scale, presented in Banker (1996), which verifies that scale return hypothesis (constant or variable) is most plausible for the data set used. Banker (1996) suggests applying the nonparametric test of two Kolmogorov-Smirnov samples based on the maximum distance of the cumulative distributions of the efficiency scores of the DEA-CRS and DEA-VRS models.

The test evaluates the null hypothesis of constant returns to scale against the alternative hypothesis of variable returns to scale. This test is based on the maximum vertical distance between $\hat{F}^c\left(\ln\left(\hat{\theta}_j^c\right)\right)$ and $\hat{F}^v\left(\ln\left(\hat{\theta}_j^v\right)\right)$; the empirical distributions of $\ln\left(\hat{\theta}_j^c\right)$ and $\ln\left(\hat{\theta}_j^v\right)$ are used. The statistic takes values between 0 and 1. Values near 1 tend to reject the null hypothesis and accept the alternative hypothesis (Banker & Natarajan, 2004).

3.3. Statistical Inference by bootstrap

Considering that DEA is a deterministic approach, a different result from the full efficiency can be interpreted as inefficiency. Among other factors, this inefficiency (or pseudo efficiency) may be due to data collection errors or factors attributed to chance, compromising estimates made about the scores (Dong & Featherstone, 2004). Aiming to correct this weakness, several studies (Efron, 1987; Xue & Harker, 1999; Löthgren & Tambour, 1999) have suggested the use of the bootstrap for more consistent results.

Bootstrap procedures produce confidence limits on the efficiencies of units to capture the true efficient frontier within the specified interval (Dyson & Shale, 2010). To correct the efficiency values, in view of the inherent random data error, the approach proposed by Simar & Wilson (1998, 2000) was used. Through this proposal, the Bootstrap technique is applied to the DEA methodology to proceed with the statistical inference of the efficiency results achieved by the DEA model (Appendix A).

Thus, for each DMU, the confidence interval of efficiency, the bias and the corrected efficiency can be estimated, which will be considered for the performance evaluation of the banks. The bootstrap bias estimate for the original DEA estimator $\hat{\theta}_{DEA}(x_0, y_0)$ can be calculated as (Equation 2):

$$\widehat{\mathrm{BIAS}}_B\left(\hat{\theta}_{DEA}(x_0, y_0)\right) = B^{-1}\sum_{b=1}^{B}\hat{\theta}^*_{DEA,b}(x_0, y_0) - \hat{\theta}_{DEA}(x_0, y_0) \tag{2}$$

Furthermore, $\hat{\theta}^*_{DEA,b(x_0,y_0)}$ are the bootstrap value and B is the number of bootstrap replications. In this way, a biased corrected estimator of $\theta(x_0, y_0)$ can be calculated as (Equation 3):

$$
\begin{aligned}
\hat{\hat{\theta}}_{DEA}(x_0, y_0) &= \hat{\theta}_{DEA}(x_0, y_0) - \widehat{BIAS}_B\left(\hat{\theta}_{DEA}(x_0, y_0)\right) \\
&= 2\hat{\theta}_{DEA}(x_0, y_0) - B^{-1}\sum_{b=1}^{B}\hat{\theta}^*_{DEA,b}(x_0, y_0)
\end{aligned}
\tag{3}
$$

According to Simar & Wilson (2000), this bias correction may create additional noise, the sample variance of bootstrap values $\hat{\theta}^*_{DEA,b}(x_0, y_0)$ need to be calculated. The calculation of the variance of the bootstrap values is illustrated below (Equation 4):

$$\hat{\sigma}^2 = B^{-1}\sum_{b=1}^{B}\left[\hat{\theta}^*_{DEA,b}(x_0, y_0) - B^{-1}\sum_{b=1}^{B}\hat{\theta}^*_{DEA,b}(x_0, y_0)\right]^2 \tag{4}$$

The bias correction illustrated in (Equation 3) needs to be avoided unless (Equation 5):

$$\frac{\left|\widehat{BIAS}_B\left(\hat{\theta}_{DEA}(x_0, y_0)\right)\right|}{\hat{\sigma}} > \frac{1}{\sqrt{3}} \tag{5}$$

4. Financial performance of banks

4.1. Data envelopment analysis

Table 3 summarizes the distribution of efficiency scores of Brazilian banks, considering the combined period (2010-2013), for the two returns to scale models, constant returns to scale and variable returns to scale.

With regards to the definition of the DEA model (constant or variable scale), literature suggests performing the Kolmogorov-Smirnov test (K-S), since the choice of technology is a key issue and if decided arbitrarily it can produce biased results. In the test procedure, the value of this statistic (0.7197) was obtained (α=1%) allowed accepting the assumption of variable returns to scale. Accordingly, Table 4 shows

Table 3. Distribution of banks per class.

Performance Class	Banks		Banks	
0.0-20%	3	10%	2	6.67%
20-40%	4	13.33%	2	6.67%
40-60%	7	23.33%	4	13.33%
60-80%	9	30%	5	16.67%
80-99%	2	6.67%	4	13.33%
100%	5	16.67%	13	43.33%
Total	30	100%	30	100%
	DEA – CRS		DEA – VRS	
Minimum	6.68		7.29	
Average	61.97		75.72	
Maximum	100		100	

Table 4. Efficiency indicators for banks.

Bank	Total	2010	2011	2012	2013	Average
ABC-Brasil	98.30	100	98.60	79.87	71.17	87.41
Alfa	100	100	93.65	90.47	100	96.03
Bancoob	100	47.76	100	100	100	86.94
Banestes	42.50	41.47	42	37.30	41.08	40.46
Banrisul	52.49	56.24	54.93	52.08	45.10	52.08
Bansicredi	100	78.62	100	100	100	94.65
Basa	27.40	32.68	33.98	32.36	23.05	30.51
Banco do Brasil	100	99.2	100	100	100	99.8
BIC	69.67	74.36	65.66	70.12	60.69	67.7
BMG	87.18	77.62	63.14	95.56	79.42	78.93
BNB	60.16	67.84	65.80	55.02	48.45	59.27
BNP Paribas	47.59	61.65	57.54	38.19	26.36	45.93
Bradesco	96.07	97.42	96.27	95.42	94.21	95.83
BRB	68.94	46.75	61.92	71.07	75.67	63.85
BTG Pactual	17.77	16.96	14.03	15.72	22.46	17.29
CEF	100	100	99.4	100	100	99.85
Citibank	27.99	32.26	31.69	26.89	22.97	28.45
Credit Suisse	100	100	100	100	54.46	88.61
Daycoval	62.28	65.83	66.42	54.52	50.94	59.42
Deutsche	100	12.30	100	40.17	18.67	42.78
Fibra	100	87.03	93.08	90.77	100	92.72
HSBC	51.48	56.25	54.51	52.46	49.69	53.22
Itaú	100	100	100	100	96.29	99.07
JP Morgan Chase	7.29	100	5.67	6.62	3.13	28.85
Mercantil do Brasil	85.21	65.41	72.38	84.44	97.85	80.02
Panamericano	69.29	100	61.57	53.47	55.41	67.61
Safra	100	95.07	100	100	79.77	93.71
Santander	100	100	100	100	98.49	99.62
Societe Generale	100	100	100	99.3	100	99.82
Votorantim	100	100	99.1	100	100	99.77
Average	75.72	73.75	74.38	71.39	67.18	71.68

the efficiencies of the banks investigated, considering the variable returns to scale for each year, as well as for the combined period.

In order to fix efficiency values, considering the random error inherent in the data, we used the classification proposed by Simar & Wilson (1998, 2000). Table 5 shows the original efficiency indicators (set on the bias), the bias and indicators corrected by the bootstrap technique. 2000 pseudo-samples generated the bootstrap results.

From the results shown in Table 5, the significant influence of the efficiency rates on the changes in the samples was found, reducing the average efficiency by 14.43%. Corrected average efficiency values, in most cases, are considerably different in magnitude when compared with the original values. Note, for example, the case of one of the largest Brazilian banks (Banco do Brasil), which after the bootstrap technique was applied, had its index corrected from 99.8% to 57.31%.

This enables verify that by conducting a purely deterministic analysis, disregarding the statistical bias influence, the results found may be overestimated.

4.2. Analysis of results

Table 6 summarizes the descriptive efficiency statistics of 30 banks. In the analysis of the disaggregated periods, a decrease in average efficiency was observed, of approximately 5.5 per cent (2010-2013).

However, it was concluded that analyzing the efficiency of all banks together could be a mistake, because of the different types of operations performed by them. Accordingly, the banks were grouped into two segments: retail banking and banks specialized in credit. This grouping followed the criteria of the Central Bank.

To observe the efficiency differences by service segment, the banks' average efficiency indicators were calculated for two service subdivisions in 2010, 2011, 2012 and 2013. It should be noted that of the 30 banks analyzed, 14 are retail banks (large public retail banks, large foreign retail banks, large private domestic retail banks and regional public retail banks) and the rest are banks specialized in credit (focused on providing few credit modalities). Table 7 shows the results.

Table 7 shows that the average efficiency of the sample decreased by 5.5%. Among the banks classified as retailers, an average decrease of approximately 3.3% was observed between 2010 and 2013. As for banks specialized in loans, there was a decrease in average efficiency. From 2010 to 2013 the decrease was of 7%. Tables 8 and 9 show performance indicators for two bank segments.

It can be observed that almost all banks specialized in loans, between 2011 and 2013, had their average efficiency indicators reduced.

In early 2012, the Federal Government concluded that Brazilian bank spreads were at much higher levels than those practiced internationally. After this, in April 2012, two major Brazilian public banks (Banco do Brasil and Caixa Econômica Federal) initiated a retraction movement in interest rates charged to loan operations. In this sense, although at much lower

Table 5. Efficiency indicators for banks after applying Bootstrap.

Bank	Average efficiency	Bias	Corrected average efficiency
ABC-Brasil	87.41	2.19	85.22
Alfa	96.03	13.60	82.87
Bancoob	86.94	24.72	62.22
Banestes	40.46	2.40	38.06
Banrisul	52.08	2.87	49.21
Bansicredi	94.65	19.50	75.15
Basa	30.51	3.25	27.26
Banco do Brasil	99.8	42.49	57.31
BIC	67.7	2.34	65.36
BMG	78.93	3.58	75.35
BNB	59.27	15.21	44.06
BNP Paribas	45.93	1.72	44.21
Bradesco	95.83	40.43	55.40
BRB	63.85	9.37	54.48
BTG Pactual	17.29	1.23	16.06
CEF	99.85	43.22	56.63
Citibank	28.45	2.95	25.50
Credit Suisse	88.61	20.82	67.79
Daycoval	59.42	0.84	58.58
Deutsche	42.78	2.65	40.13
Fibra	92.72	10.41	82.31
HSBC	53.22	9.08	44.14
Itaú	99.07	42.83	56.24
JP Morgan Chase	28.85	8.73	20.12
Mercantil do Brasil	80.02	15.41	64.61
Panamericano	67.61	0.75	66.86
Safra	93.71	18.03	75.68
Santander	99.62	43.64	55.98
Societe Generale	99.82	11.02	88.80
Votorantim	99.77	17.98	81.79
Average	71.67	14.43	57.25

Table 6. Descriptive statistics of efficiency indicators of 30 banks.

Descriptive Statistics	2010	2011	2012	2013
Average	57.70	59.88	56.88	54.53
Mean	56.69	58.33	56.71	56.77
Standard-Deviation	20.39	21.72	21.21	22.72
Maximum	92.87	92.21	90.03	89.73
Minimum	6.19	7.23	7.74	5.83

Table 7. Efficiency average by segment.

	2010	2011	2012	2013
Total sample	57.70	59.88	56.88	54.53
Retail banks	50.70	51.13	50.44	49.02
Banks specialized in credit	63.81	67.53	62.50	59.35

Table 8. Efficiency indicators of retail banks.

Banks	2010	2011	2012	2013
Banco do Brasil	56.87	57.30	56.98	58.09
Bradesco	56.89	55.35	53.95	55.40
CEF	56.19	56.62	56.30	57.41
Itaú	56.33	56.76	56.44	55.44
Santander	55.76	56.19	55.87	56.12
Banrisul	56.02	54.95	47.88	37.98
BNB	48.59	47.74	41.52	38.39
Citibank	30.07	25.75	26.03	20.16
HSBC	45.59	44.86	43.54	42.55
Safra	75.92	80.22	78.46	68.12
Banestes	43.13	37.53	34.50	37.06
Basa	28.35	29.21	28.20	23.27
Mercantil do Brasil	56.51	59.36	67.39	75.17
BRB	43.67	53.97	59.11	61.17

intensity, private banks (retail and specialized in credit), followed suit in this retraction movement of rates.

However, it should be noted that Brazil has a large bank concentration, in which six banks hold over 80% of the market share (Departamento Intersindical de Estatística e Estudos Socioeconômicos, 2013), of which two are the major Brazilian public banks.

Between April 2012 and January 2013, the operations for natural persons underwent significant changes in their rates. Two major Brazilian public banks reduced the overdraft rate by an average of 43%, while for the personal credit line the average reduction by private banks was of 3.75%; the mean reduction in two public banks was of 26%, and in the private banks the average reduction was of 14.5%; and for the auto loan financing the average reduction was of 31.5% for public banks and 22% for the banks investigated (Departamento Intersindical de Estatística e Estudos Socioeconômicos, 2013).

With regards to the credit lines for companies, the mean rate reductions also differed between public and private banks. For promissory note discounts, the public banks offered average reductions of 34.5%; while the average reduction by private banks was of 13.5%. For working capital finance, the average reduction of public banks was of 40% and in private banks it was of 19.5% (Departamento Intersindical de Estatística e Estudos Socioeconômicos, 2013).

By monitoring the retractions in interest rates, there was, as expected, an increase in credit operations throughout the Brazilian banking system. According to the data from the Departamento Intersindical de Estatística e Estudos Socioeconômicos (2013), it can be observed that the operations of the public financial system grew by 28.2% in 12 months (Dec/2011 to Dec/2012). In the same period, the operations of the domestic private financial system and foreign institutions grew only 6.7% and 8.5%, respectively.

It can then be understood why so many of the loan specialized banks underwent the greatest reduction in average efficiency during the period investigated. They increased their resources (the number of employees, deposits and capital) and the credit operation growth fell short of what was feasible. This result is due to the decrease in interest rates, initiated by two major Brazilian public banks which virtually dominated the expansion of loan operations within this period.

The loan specialized banks had higher average efficiency indicators than that of the retail banks, and this is the result of their higher input productivity in relation to the loan operations generated by these institutions. In other words, public banks and retail banks may generate greater loan operation activities (both in the number of operations as well as financial resources), but their resources (employees, deposits, and capital) are less productive than the resources of banks specialized in credit.

The DEA analysis does not consider the size of a unit to classify it as efficient – what is considered in this type of analysis is the use of resources (inputs) to achieve the product (outputs). Efficiency is the relationship between the results obtained and the resources used. Accordingly, managerial aspects (resource allocation decisions) are more relevant in the DEA analysis than the size of the decision making unit.

Tables 10 and 11 identify the less efficient banks, considering the segment in which they operate. For the Retail Bank category, the least efficient bank was Citibank, and for the Banks Specialized in Credit category, JP Morgan was the most inefficient.

For Citibank, the DEA suggests another bank as a benchmark, the Safra bank (both mid-sized). Comparing Citibank to Safra enables identify the

Table 9. Efficiency indicators for banks specialized in credit.

Banks	2010	2011	2012	2013
ABC-Brasil	92.87	92.21	79.74	76.08
Alfa	82.24	80.00	79.76	89.49
Bancoob	44.19	83.66	61.78	59.25
BIC	71.00	64.84	64.85	60.75
BMG	73.88	61.09	85.59	80.82
BNP Paribas	54.36	53.12	39.62	29.72
BTG Pactual	15.79	14.22	15.12	19.12
Credit Suisse	64.71	74.18	80.23	52.03
Deutsche	6.19	81.83	45.14	27.38
Fibra	79.07	84.61	78.92	86.65
JP Morgan Chase	59.70	7.23	7.74	5.83
Panamericano	84.57	66.66	58.06	58.15
Votorantim	79.75	78.15	82.75	86.50
Bansicredi	65.72	84.85	75.04	75.00
Daycoval	61.52	63.92	55.74	53.13
Societe Generale	85.42	90.03	90.03	89.73

Table 10. Citibank × Safra.

	Citibank	Safra
Average efficiency (%)	25.50	75.68
Deposits (R$)	62.579.957	52.290.920
Net equity (R$)	27.623.372	26.014.704
Number of employees	6.190	5.753
Credit operations (R$)	51.511.037	156.610.079

Table 11. JP Morgan × Alfa.

	JP Morgan	Alfa
Average efficiency (%)	20.12	82.87
Deposits (R$)	6.504.849	8.141.772
Net equity (R$)	11.353.675	7.619.346
Number of employees	737	888
Credit operations (R$)	1.439.015	26.979.487

under-utilization of some resources by the first bank. Table 10 describes some of the data.

Using the DEA technique enabled estimate the growth potential of Loan Operations, from the observed input levels of Citibank. This bank could increase its output by 215%, considering its resources available each year. Table 11 displays the comparison between JP Morgan and its benchmark, the Alpha Bank (both mid-sized).

The JP Morgan bank, given the resources employed had the potential to expand its lending operations by more than 1000% in the overall period.

Table 12 was prepared from these results in order to establish the following relationships: credit operations/deposits, credit operations/total assets and credit operations/employees.

Table 12 enables identify the productivity of the variables of the model and verify the reason why some banks are considered more efficient than others. For example, if the efficiency of a bank were exclusively dependent on the relationship between deposits and operations, the Alpha Bank would be more efficient, since each deposit unit, of this bank, is converted into 3.31 units of loan operations. Accordingly, the least efficient would be JP Morgan (0.22). In the "Credit Operation/Total Assets" relation, the most efficient bank was Sicredi, since each total assets unit produced 15.83 units of loan operations and, again, the least efficient was JP Morgan (0.13). And finally, if bank efficiency were to be defined only by the productivity of employees, the Credit Suisse bank would have been the most efficient, with each employee having produced 390.806 units of credit operations. JP Morgan would again be the least efficient (1.954).

Of the top five retail banks operating in the country (Banco do Brasil, Caixa Econômica Federal, Bradesco, Itaú and Santander), the most productive bank, considering only the "deposits" feature, was Santander; considering only the "total assets" feature, it was Caixa Econômica Federal; and considering only the "employees" feature, it was Banco do Brasil.

By demonstrating that a bank is more efficient in some variables (Table 11) than others, we do not state that the situation of the bank model is ideal, since there is no consensus in the literature about

Table 12. Data banks.

Banks	Credit Operations/Deposits	Credit Operations/ Total Assets	Credit Operations/Employees
ABC-Brasil	2.24	4.71	55.81
Alfa	3.31	3.54	30.39
Bancoob	0.48	11.16	45.15
Banestes	0.51	3.95	3.75
Banrisul	0.85	4.63	7.13
Bansicredi	0.93	15.83	95.45
Basa	0.83	1.15	2.20
Banco do Brasil	1.00	7.38	13.78
BIC	1.27	5.26	45.79
BMG	1.96	4.54	94.06
BNB	1.16	4.56	3.46
BNP Paribas	1.17	2.24	38.57
Bradesco	1.16	4.04	10.22
BRB	0.83	6.51	5.24
BTG Pactual	0.44	0.81	23.93
CEF	1.08	14.24	10.75
Citibank	0.82	1.86	8.32
Credit Suisse	1.16	1.18	390.80
Daycoval	1.77	3.27	26.75
Deutsche	0.43	1.03	17.49
Fibra	1.37	7.39	48.73
HSBC	0.73	5.16	6.31
Itaú	1.20	3.85	9.69
JP Morgan Chase	0.22	0.13	1.95
Mercantil do Brasil	0.97	8.75	7.26
Panamericano	1.31	4.79	53.07
Safra	2.99	6.02	27.22
Santander	1.39	2.64	13.10
Societe Generale	2.42	2.95	23.03
Votorantim	2.95	6.73	131.93

the "optimal capacity" of such specific production factors. Therefore, when we declare, for example, that the Credit Suisse bank is the most efficient, considering only the credit operations by employees, we are only saying that the employees of this bank are more productive in comparison to the employees of the other 29 banks.

Bank efficiency is related to the balance between the input resources (employees, financial resources, structure and equipment necessary for a bank's operation, and etc.) and output resources (loan operations, income from financial intermediation, and etc.), for the quality of such services, among other factors.

The analysis proposed in this work was purely about financial intermediation, which showed that all the banks investigated can and should improve the performance of their production resources. However, we delimit the conclusions to the sample investigated, quite aware that if the comparison undertaken encompassed large banks from different countries, Brazilian banks would admittedly be more distant from the efficient frontier.

5. Final Remarks

This paper proposes measuring the efficiency of 30 Brazilian banks using the data envelopment analysis methodology. This technique was applied to a set of banks in 2010, 2011, 2012 and 2013.

The concept of efficiency has traditionally been related to the reason "output / input" of investigated units. The unit that generates more output with fewer resources, is considered the most efficient. In configurations of multiple inputs and output, the allocation of weights to the inputs and output is required in order to calculate the efficiency of production units. The DEA is a nonparametric technique that uses linear programming to determine optimal weights that minimize the distance between the efficient frontier and the unit investigated.

The main advantage of DEA is that it does not require the specification of a production function. The DEA uses a set of inputs that the unit wants to minimize and a set of output that the unit wants to maximize. The disadvantage of the technique is that the statistical inference is very difficult to apply in efficiency scores. Therefore, the DEA bootstrap procedure (Simar & Wilson, 1998) allows extraction of the sensitivity of scores stemming from sample distribution inefficiency.

In this direction, we seek to benefit from the advantages of using DEA and take care of what we consider the fragility of it, through the use of DEA bootstrap.

It should be emphasized that the results obtained do not refer to absolute efficiency. The banks considered efficient are only classified this way for the group analyzed.

In this work, the matter of the best classification among retail banks and banks specialized in credit has little relevance. The low relevance in this type of comparison is a result of analysis by segments (segments were analyzed separately). The data envelopment analysis allows to calculate the efficiency indicators of homogeneous units and of different sizes. However, even for banks of different sizes, it was understood that they were not effectively homogeneous, since they operate in different niches and therefore perform different operations. Accordingly, the classification of efficient retail banks is completely set apart from the classification of banks specialized in credit. Therefore, in this analysis the efficiency increase gains more emphasis to each segment investigated.

In September 2012, the Valor Econômico newspaper published an article entitled "With falling interest rates, banks pursue efficiency gains" (Mandl, 2012) and reported some efficiency results of large Brazilian banks. The paper discusses the results reported by Goldman Sachs, declaring that compared to their peers around the world, Brazilian banks were the least efficient.

The results presented here, although only addressing Brazilian reality, point to an average level of efficiency for the large Brazilian banks in the period analyzed – which somehow corroborates the results reported by Goldman Sachs, when referring to the efficiency of large Brazilian banks. This is a new scenario, which not only requires efforts to reduce expenses but also to increase revenues, even taking into consideration reduced interest rates which result in lower earnings for banks.

References

Banker, R. D. (1996). Hypothesis tests using data envelopment analysis. *Journal of Productivity Analysis*, *7*(2-3), 139-159. http://dx.doi.org/10.1007/BF00157038.

Banker, R. D., & Natarajan, R. (2004). Statistical tests based on DEA efficiency scores. In W. Cooper, L. Seiford, & J. Zhu (Eds.), *Handbook on data envelopment analysis* (pp. 265-298). New York: Kluwer Academic Publishers.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, *30*(9), 1078-1092. http://dx.doi.org/10.1287/mnsc.30.9.1078.

Berger, A. N., & Humphrey, D. B. (1992). Measurement and efficiency issues in commercial banking. In Z. Griliches, *Output measurement in the service sectors* (pp. 175-212). Chicago: University of Chicago Press.

Berger, A. N., & Humphrey, D. B. (1997). Efficiency of financial institutions: international survey and directions for future research. *European Journal of Operational Research*, *98*(2), 175-212. http://dx.doi.org/10.1016/S0377-2217(96)00342-6.

Charnes, A., Cooper, W., Lewin, A. Y., & Seiford, L. M. (1994). *Data envelopment analysis: theory, methodology, and application*. Boston: Kluwer Academic Publishers.

Departamento Intersindical de Estatística e Estudos Socioeconômicos – DIEESE. (2013). *Um novo cenário para o setor financeiro no Brasil* (Nota Técnica, 123, pp. 1-15). São Paulo: DIEESE. Retrieved in 23 October 2013, from http://www.dieese.org.br/notatecnica/2013/notaTec123CenarioSetorFinanceiro.pdf

Dong, F., & Featherstone, A. (2004). *Technical and scale efficiencies for Chinese rural credit cooperatives: a bootstrapping approach in data envelopment analysis* (Working Paper, 04 WP-366). Iowa: Center for Agricultural and Rural Development. 26 p. Retrieved in 23 October 2013, from http://www.researchgate.net/publication/24085100_Technical_and_Scale_Efficiencies_for_Chinese_Rural_Credit_Cooperatives_A_Bootstrapping_Approach_in_Data_Envelopment_Analysis

Drake, L., & Hall, M. J. B. (2003). Efficiency in Japanese banking: an empirical analysis. *Journal of Banking & Finance*, *27*(5), 891-917. http://dx.doi.org/10.1016/S0378-4266(02)00240-6.

Dyson, R. G., & Shale, E. A. (2010). Data envelopment analysis, operational research and uncertainty. *The Journal of the Operational Research Society*, *61*(1), 25-34. http://dx.doi.org/10.1057/jors.2009.145.

Efron, B. (1987). Better bootstrap confidence intervals. *Journal of the American Statistical Association*, *82*(397), 171-185. http://dx.doi.org/10.1080/01621459.1987.10478410.

Fukuyama, H., & Matousek, R. (2011). Efficiency of Turkish banking: two-stage network system. Variable returns to scale model. *Journal of International Financial Markets, Institutions and Money*, *21*(1), 75-91. http://dx.doi.org/10.1016/j.intfin.2010.08.004.

Gaganis, C., Liadaki, A., Doumpos, M., & Zopounidis, C. (2009). Estimating and analyzing the efficiency and productivity of bank branches: evidence from Greece. *Managerial Finance*, *35*(2), 202-218. http://dx.doi.org/10.1108/03074350910923518.

Giokas, D. (2008). Assessing the efficiency in operations of a large Greek bank branch network adopting different economic behaviors. *Economic Modelling*, *25*(3), 559-574. http://dx.doi.org/10.1016/j.econmod.2007.10.007.

Halkos, G. E., & Salamouris, D. S. (2004). Efficiency measurement of the Greek commercial banks with the use of financial ratios: a data envelopment analysis approach. *Management Accounting Research*, *15*(2), 201-224. http://dx.doi.org/10.1016/j.mar.2004.02.001.

Halkos, G. E., & Tzeremes, N. G. (2013). Estimating the degree of operating efficiency gains from a potential bank merger and acquisition: A DEA bootstrapped approach. *Journal of Banking & Finance*, *37*(5), 1658-1668. http://dx.doi.org/10.1016/j.jbankfin.2012.12.009.

Löthgren, M., & Tambour, M. (1999). Testing scale efficiency in DEA models: a bootstrapping approach. *Applied Economics*, *31*(10), 1231-1237. http://dx.doi.org/10.1080/000368499323445.

Macedo, M. A. S., & Barbosa, A. C. M. (2009). Eficiência no sistema bancário Brasileiro: uma análise do desempenho de bancos de varejo, atacado, middle-market e financiamento utilizando DEA. *Revista de Informação Contábil*, *3*, 1-24.

Mandl, C. (2012, September 3). *Com juros em queda, bancos perseguem ganhos de eficiência*. Valor Econômico: Caderno de Finanças. Retrieved in 23 October 2013, from http://www.valor.com.br/financas/2814064/com-juros-em-queda-bancos-perseguem-ganhos-de-eficiencia/#comments

Paradi, C. P., Rouatt, S., & Zhu, H. (2011). Two-stage evaluation of bank branch efficiency using Data Envelopment Analysis. *Omega*, *39*(1), 99-109. http://dx.doi.org/10.1016/j.omega.2010.04.002.

Pastor, J. T., Lovell, C. A. K., & Tulkens, H. (2006). Evaluating the financial performance of bank branches. *Annals of Operations Research, Louvain-la-Neuve*, *145*(1), 321-337. http://dx.doi.org/10.1007/s10479-006-0038-3.

Périco, A. E., Rebelatto, D. A. N., & Santana, N. B. (2008). Eficiência bancária: os maiores bancos são os mais eficientes? Uma análise por envoltória de dados. *Gestão & Produção*, *15*(2), 421-431. http://dx.doi.org/10.1590/S0104-530X2008000200016.

Portela, M., & Thanassoulis, E. (2007). Comparative efficiency analysis of Portuguese bank branches. *European Journal of Operational Research*, *177*(2), 1275-1288. http://dx.doi.org/10.1016/j.ejor.2006.01.007.

Sealey, C. Jr, & Lindley, J. T. (1977). Inputs, outputs and a theory of production and cost at depository financial Institutions. *The Journal of Finance*, *32*(4), 1251-1266. http://dx.doi.org/10.1111/j.1540-6261.1977.tb03324.x.

Simar, L., & Wilson, P. (2000). A general methodology for bootstrapping in nonparametric frontier models. *Journal of Applied Statistics*, *27*(6), 779-802. http://dx.doi.org/10.1080/02664760050081951.

Simar, L., & Wilson, P. W. (1998). Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models. *Management Science*, *44*(1), 49-61. http://dx.doi.org/10.1287/mnsc.44.1.49.

Stavarek, D. (2005). Estimation of Factors Influencing Efficiency of Banks in New Member States before Joining the European Union. *Ekonomicky Casopis*, *53*, 593-610.

Xue, M., & Harker, P. T. (1999). *Overcoming the inherent dependency of DEA efficiency scores: a bootstrap approach* (Working Paper, 99-17). The Wharton Financial Institutions Center.

Appendix A. Bootstrap procedures.

This appendix illustrates the bootstrap-based algorithm introduced by Simar & Wilson (1998, 2000). The procedure is as follows:

- Step 1: Transform the input-output vectors using the original efficiency estimates: $\left\{\hat{\theta}_{in}, i=1,\ldots,n\right\} as \left(\hat{x}_i^l, y_i\right) = \left(x_i \,.\hat{\theta}_{in}, y_i\right)$
- Step 2: Generate smoothed resampled pseudo-efficiencies y_i^* as follow: Step 2.1: Given a set of estimated efficiencies $\left\{\hat{\theta}_{in}\right\}$, use the "rule of thumb" (Silverman, 1986, p. 47-48) to obtain the bandwidth parameter h as $h = 0.9$ $^{1/5}$ $\min\left\{\hat{\sigma}_{\hat{\theta}}, R_{13}/1.34\right\}$, where $\hat{\sigma}_{\hat{\theta}}$ is the standard deviation of $\left\{\hat{\theta}_{in}\right\}$ and R_{13} is the interquartile range of the empirical distribution of $\left\{\hat{\theta}_{in}\right\}$.
- Step 2.2: Generate $\left\{\delta_i^*\right\}$ by replacing, with replacement, from the empirical distribution of $\left\{\hat{\theta}_{in}\right\}$ estimated efficiencies.
- Step 2.3: Generate the sequence $\left\{\tilde{\delta}_i^*\right\}$ using:

$$\left\{\tilde{\delta}_i^*\right\} = \begin{cases} \delta_i^* + h\varepsilon_i^* & if\ \delta_i^* + h\varepsilon_i^* \le 1 \\ 2 - \left(\delta_i^* + h\varepsilon_i^*\right) & otherwise \end{cases}$$

where ε_i^* is drawn i.i.d.. from a standard normal distribution.

- Step 2.4: Generate smoothed pseudo-efficiencies $\left\{\gamma_i^*\right\}$ using the following formula:

$$\gamma_i^* = \frac{\bar{\delta}_i^*\left(\tilde{\delta}_i^* - \bar{\delta}_i^*\right)}{\sqrt{1 + h^2/\hat{\sigma}_{\hat{\theta}}^2}},$$

where $\bar{\delta}_i^* = \sum_{i=1}^{n} \delta_i^* / n$, which is the average of the resampled original efficiencies.

- Step 3: Let the pseudo-data be given by:

$$(x_i^*, y_i^*) = (\hat{x}_i^l / \gamma_i^*, y_i)$$

- Step 4: Estimate the bootstrap efficiencies using the pseudo-data as:

$$\hat{\theta}_{in}^{SW*} = min_{\theta,z}\left\{\theta : y_i \le Yz, \theta x_i \ge X^* z, \sum_{i=1}^{n} z_i = 1,\ z \in R_+^n\right\}$$

- Step 5: Repeat steps (2)-(4) 2000 times to create a set of 2000 bank-specific bootstrapped efficiency estimates

$$\hat{\theta}_{in}^{SW*b}, i = 1,\ldots,n, b = 1,\ldots,2000.$$

References

Silverman, B. W. (1986). *Density estimation for statistics and data analysis: monographs on statistics and applied probability*. London: Chapman & Hall.

Simar, L., & Wilson, P. W. (1998). Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models. *Management Science*, *44*(1), 49-61. http://dx.doi.org/10.1287/mnsc.44.1.49.

Simar, L., & Wilson, P. (2000). A general methodology for bootstrapping in nonparametric frontier models. *Journal of Applied Statistics*, *27*(6), 779-802. http://dx.doi.org/10.1080/02664760050081951.