https://doi.org/10.3926/hdbr.256

# Empirical Evaluation of the Efficiency of the Ecuadorian Banking Sector

**Jorge Arturo Campoverde Campoverde**
Coordinator of the Business Research Group. Master's degree in Business Administration. Principal Investigator and Professor of Operations Research at the Universidad de Cuenca. Ecuador.
ORCID: 0000-0002-1633-5644.

**Gustavo Giovanni Flores Sánchez**
Investigator and professor of finance management at the Universidad de Cuenca. Ecuador.
ORCID: 0000-0003-4123-2644.

**Katherine Tatiana Coronel Pangol**
Junior Investigator in the Business Research Group at the Universidad de Cuenca. Ecuador.
ORCID: 0000-0003-4370-756X.

**Carlos Armando Romero Galarza**
Junior Investigator in the Business Research Group at the Universidad de Cuenca. Ecuador.
ORCID: 0000-0003-1149-4299.

jorge.campoverde@ucuenca.edu.ec, gustavo.flores@ucuenca.edu.ec, katherine.coronelp95@ucuenca.edu.ec, armando.romerog@ucuenca.edu.ec

Received: November 2019.
Accepted: December 2019.
Published: June 2020.

## Abstract
This research constitutes the measurement of the efficiency of the Ecuadorian banking sector during the periods 1993-1999 and 2000-2018, applying the Data Envelope Analysis methodology, using the CCR and BCC approaches. The fixed asset and operating expense accounts were used as input variables for this purpose. The output variables were accounts receivable, income, investments and total deposits. Data were taken from monthly bulletins submitted by the different decision-making units to the *Superintendencia de Bancos del Ecuador*. The main findings indicate that the levels of efficiency during the 2000-2018 period were higher than in the 1993-1999 period. On average, during the first period, the banks had an efficiency ratio of 74.31%, according to the CCR approach, and 82.17%, according to the BCC approach. However, the efficiency levels during the second period reached 95.43% and 97.01%, respectively. In addition, the results show that large banks have a higher level of efficiency than smaller banks. However, medium-sized banks have the lowest level of efficiency. It should be noted that the data varies when analyzed according to the CCR approach. Furthermore, efficiency levels are generally associated with factors related to the country's situation. This research is presented as one of the first studies on the analysis of efficiency in the Ecuadorian banking sector using this method.

## Key words
Efficiency, Banking System, Data Envelopment Analysis, Decision-Making Units, DEA.

## How to cite this article

Campoverde Campoverde, J. A., Flores Sánchez, G. G., Coronel Pangol, K. T., & Romero Galarza, C. A. (2020). Empirical Evaluation of the Efficiency of Ecuadorian Banking Sector. *Harvard Deusto Business Research,* IX(1), 20-39. https://doi.org/10.3926/hdbr.256

**We analyze efficiency of the banking sector to investigate the behavior and efficiency achieved by the banking institutions that operated in the country, before and after the currency substitution**

## 1. Introduction

The efficiency analysis in different types of organizations (financial, educational, health care, governmental, etc.) constitutes a very relevant topic, since the results obtained facilitate decision-making by the directors of each institution, in which proper resource assignment and an increase in investments promote economic growth (Andrieş & Cocriş, 2010). This is particularly true in financial institutions, where this type of study, like profitability and risk analyses, is highly applicable to different countries around the world. Berger and Mester (1997) state that efficiency analyses in the banking sector constitute an important contribution from a micro- and macroeconomic perspective. In the field of microeconomics, this is due to their impact at the organizational level of each bank, helping them to increase their competitiveness (Koutsomanoli-Filippaki, Margaritis & Staikouras, 2009); and on the macroeconomic level, the efficiency of the banking system has an influence on the cost of intermediation and on the overall financial stability of the banking sector (Rossi, Schwaiger & Winkler, 2005).

In this context, we deemed the efficiency analysis of this sector to be a necessary and important contribution to Ecuadorian literature, given the need to know the performance and efficiency achieved by the banking institutions that operated in the country before and after the currency substitution (replacing the sucre with the United States dollar) that occurred in the country in 2000, as the result of the 1999 bank holiday. It is also important to study the effects that the international financial crisis of 2008 could have had on the national banking system.

The aim of this study is to measure the efficiency of the Ecuadorian banking sector, examining certain parameters and/or variables of each institution, such as: costs, resource allocation, performance, etc., by measuring the technical efficiency (TE) and pure technical efficiency (PTE) during the periods 1993-1999 and 2000-2018, applying the Data Envelopment Analysis (DEA) methodology, thus obtaining ratios that would make it possible to determine the efficient and inefficient Decision-Making Units (DMU). The efficiency of each bank is calculated by comparing its inputs and outputs to the rest of the banks (Arieu, 2004).

Another aim is to study the evolution and behavior individually and on a group basis for the financial institutions based on their size: large, medium and small, classified based on their total assets. In this context, the research questions are: (i) Has the efficiency of the banking sector increased over time? (ii) In which period are the banks more efficient (in the era of the sucre or with the dollar)? (iii) Are large banks more efficient? (iv) Can these findings provide relevant information for decision-making by owners and administrators of banking institutions?

The article is structured as follows: the first part succinctly reports the most important events occurring in the Ecuadorian banking sector before and after the currency substitution and the reasons why we conducted this investigation. The second section shows several cases analyzed based on the application of the DEA model to the banking sector in different countries, which will serve as the reference literature in order to conduct the research. The third section

**This study constitutes one of the first approaches to an updated and retrospective efficiency analysis of the financial sector, using non-parametric methods**

indicates the methodology and the description of the analysis models used. The fourth section presents the results obtained, while the final part addresses the conclusions derived from the investigation. The previous literature has made it possible to identify a work related to the topic of analysis (Buenaño, 2004), which analyzed the efficiency of 18 institutions in the Ecuadorian banking sector during the period 2000-2003, from the perspective of DFA (Distribution Free Approach); however, no similar works have been found in recent years, and thus the present study constitutes one of the first approaches to the analysis of the efficiency of the financial sector that is both up-to-date and retrospective, through the use of non-parametric methods for this purpose. It constitutes an interesting starting point for the later study of efficiency in different sectors and its evolution within the same sector.

### 1.1. Previous literature

Efficiency is directly related to the productive capacity and/or the capacity to carry out a job with a certain amount of resources. It is measured according to variables that evaluate the relationship between results and the resources invested. To do this, different methods with focuses on parametric and non-parametric data have allowed us to measure the efficiency of several types of institutions, including financial, educational, health care, service provision, commercial and other institutions, in both the public and private sector (Navarro & Torres, 2006). The measurement of efficiency constitutes a topic of great importance in the different institutions in which the use of DEA methodology is considered a useful factor for decision-making (Valencia & Chediak, 2008; Restrepo & Villegas, 2011). The studies conducted on this topic have been generated subsequent to the work done by Farrell (1957).

The DEA method, known as Data Envelopment Analysis, is based on an approach that uses numerical input and output data, which makes it possible to estimate the efficiency ratios for each of the units of analysis or DMUs. This technique was developed by Charnes, Cooper and Rhodes (1978) and is defined as a model applied under the assumption of constant returns to scale (CRS), also known as CCR, after the names of its authors; it was later improved by Banker, Charnes and Cooper (1984), who included the assumption of variable returns to scale (VRS), thus modifying the original linear programming model, also known as BCC, after the names of its authors.

The adaptation of the VRS model permitted the authors to define the technical efficiency (TE) according to two concepts known as pure technical efficiency (PTE) and scale efficiency (SE), for which the CRS and VRS models should be applied, respectively. TE coincides with the CRS or CCR measurement and PTE with the VRS or BCC measurement (Navarro & Torres, 2006).

Initially, the model was used to measure the efficiency of production of a single unit of analysis, and was later expanded to the analysis of several units in different types of organizations (Cooper, Seiford & Tone, 2007). This methodology has also been commonly used in finance analysis to evaluate efficiency (Board, Sutcliffe & Ziemba, 2003; Fethi & Pasiouras, 2010); as an example of how the model has been applied, it has been generally used in different countries to measure the efficiency values of institutions in the financial sector, including banks and cooperatives (Andrieş & Cocriş, 2010; Favero & Papi, 1995; Joseph & Pastory, 2013; Asawaruangpipop & Suwunnamek, 2014; Xueping, Jie & Hongxin, 2011; Nitoi, 2009; Radojka, Marija & Predrag, 2013; Belmonte & Plaza, 2008; Pirateque, Piñeros & Mondragón, 2013; Vilela, Nagano & Merlo, 2007; Borenstein, Luiz Becker & José do Prado, 2004). In addition to the works by these authors, we can add that by Lozano, Pastor and Pastor (2002), which reveals that most of the studies are focused on the efficiency analysis of banks. DEA has also been used in almost every banking system in the world. Tanna (2009) has used this methodology to analyze a group of world banking institutions. Many studies were

**The DEA method represents an extremely useful tool when studying the relative efficiency of different economic entities, when both output and input variables are used**

conducted in countries belonging to the European Union (Casu & Molyneux, 2003), and some were also carried out in developing countries. In this sense, we can cite several examples of the use of this methodology: Idries (2007) uses DEA in a study investigating the levels of profitability in the banking sectors of several Arab countries, including Jordan, Egypt, Saudi Arabia and Bahrain, during the period 1992-2000. The main purpose of this research is focused on conducting a comparative analysis of the performance of the banking operations with their counterparts in the most highly developed nations. The study highlights the characteristics associated with the roles of economic and financial development, considering a sample of 82 banks representing 78%, 88%, 63% and 55% of the financial system in these countries, respectively. As a result, they determined that the profitability of the banks being studied was on average 50%, when the estimate was made according to constant returns to scale models and ascended to 70% according to the variable returns to scale model.

Other evidence that can be cited is the analysis of the banking sector in India, where Karimzadeh (2012) estimates the technical efficiency and total efficiency of the economy of commercial banks in the period 2000-2010. He uses the CCR and BCC models applied to India's 8 largest commercial banks. As a result of determining the efficiency ratios, it is generally indicated that in the year 2000, the efficiency was 100%, and that this fluctuated to lower percentages in later years, until reaching the level of 100% once again in 2010. It was also generally determined that the profitability of the banks studied was on average 93% when estimated according to constant returns to scale (CRS) models, and reached 99% with variable returns to scale (VRS) models. Similar analyses have been made in the state of Missouri, where the DEA model was used to evaluate the management of 64 commercial banks during the period 1984-1990 (Yue, 1992). The research consisted of measuring the TE by applying the CCR model. This made it possible to obtain details of the efficiency ratios of the banks, which were used to make comparisons between the different variables that affect the levels of efficiency.

Finally, one example considered for research is the analysis of the banking sector in Bangladesh, where Hoque and Rayhan (2012) analyzed the technical efficiency, pure technical efficiency and scale efficiency of a total of 24 banks during 2010. In Latin America, one related study is that conducted by Carreño, Loyola and Portilla (2010), which characterized the evolution of the efficiency of the Chilean banking industry between 1987 and 2007, based on a performance frontier report; in this sense, one of the main results indicates that this sector has achieved only 15% of its maximum earnings, which is presented as the cause of technical shortcomings in the sector, which affect small, national banks to a larger extent. The DFA method was used for this analysis. Furthermore, Vergara (2006) proposes an analysis to estimate the stochastic frontiers of the Chilean banking sector, in which the technical efficiency is estimated through three functional forms: the Fourier flexible, Translog and Cobb Douglas forms, determining that the latter tends to underestimate efficiency. It is also indicated that the non-parametric models can be effective to determine efficiency and stochastic frontiers.

In short, the DEA method represents an extremely useful tool for studying the relative efficiency of different economic institutions, in which outputs and inputs are used as variables, applying this methodology in different sectors, such as health care, education, transportation, industry, banking, etc. Emrouznejad (2015) has provided information related to the DEA methodology, which can be found at: http://www.deazone.com/.

## 2. Methodology

Throughout history, many different techniques have been used to determine efficiency. Some have been based on the analysis of indicators, while others compare the efficiency of



Harvard Deusto Business Research. Volume IX. Issue 1. Pages 20-39. ISSN: 2254-6235

**DEA methodology allows for different approaches to be taken, either input or output, depending on the optimization objective, and also determines an efficient production frontier**

organizations, considering the application of various inputs that will generate various outputs. These efficiency techniques have been divided into two categories, the first of which corresponds to linear programming models (DEA), while the second category refers to regression techniques called stochastic frontier analysis (SFA).

The use of DEA methodology makes it possible to have different focuses, either input or output, depending on the optimization aim, also specifying an envelopment surface or efficient production frontier. DEA methodology has been validated in the analysis sector by several studies (Andrieş & Cocriş, 2010; Benavides & García, 2014; Radojka et al., 2013; Vilela et al., 2007). In addition, it is applicable to case studies, as it analyzes homogeneous units and considers information and variables defined as inputs and outputs.

Cooper et al. (2007) propose the following methodological description of the CCR and BCC models.

## 2.1. CCR (*CRS*) model

This is considered the basic model of the DEA methodology, which starting with the information, relates corresponding data to their input and output variables, determining the optimal weight of each DMU through the use of linear programming to maximize the ratios obtained.

The weights are determined according to the following formula:

$$\frac{\text{virtual output (U)}}{\text{virtual input (V)}}$$

The weights obtained can vary from one DMU to another, and thus the model derives the efficiency ratio obtained on an individual basis; each DMU is compared simultaneously with a set of weights obtained for the other DMUs.

With the data from each DMU, the efficiency is determined by calculating (n) optimizations, one for each $DMU_j$ being evaluated, permitting each $DMU_j$ to be designated as $DMU_o$, where o = 1, 2, 3 up to n. The optimization problem is resolved with the approach that considers the input variables as ($V_i$) (i = 1, ... m) and the output variables as ($U_r$) (r = 1, ... s).

Objective function:

$$\max_{u,v} \theta = \frac{u_1 y_{1_0} + u_2 y_{2_0} + \dots\dots + u_s y_{s_0}}{v_1 x_{1_0} + v_2 x_{2_0} + \dots\dots + v_m x_{m_0}} \qquad (1)$$

Subject to:

$$\frac{u_1 y_{1_j} + \dots + u_s y_{s_j}}{v_1 x_{1_j} + \dots + v_m x_{m_j}} \leq 1 \; (j = 1, \dots, n) \qquad (2)$$

To measure efficiency, the objective function is transformed into a linear programming problem in which the numerator is maximized

$$v_1, v_2, \ldots\ldots., v_m \geq 0 \tag{3}$$

$$u_1, u_2, \ldots\ldots., u_s \geq 0 \tag{4}$$

To measure the efficiency, the objective function is transformed into a linear programming problem, where the numerator is maximized and the denominator is kept constant.

Objective function:

$$\max_{u,v} \theta = u_1 y_{1_O} + u_2 y_{2_O} + \ldots \ldots \ldots + u_s y_{s_O} \tag{5}$$

Subject to:

$$v_1 x_{1_O} + v_2 x_{2_O} \ldots \ldots \ldots + v_m x_{m_O} = 1 \tag{6}$$

$$u_1 y_{1_j} + \ldots \ldots \ldots + u_s y_{s_j} \leq v_1 x_{1_j} + v_2 x_{2_j} + \ldots \ldots \ldots + v_m x_{m_j} \ (j = 1, \ldots, n) \tag{7}$$

$$V_1, V_2, \ldots\ldots., V_m \geq 0 \tag{8}$$

$$u_1, u_2, \ldots\ldots., u_s \geq 0 \tag{9}$$

## 2.2. BCC (*VRS*) model

This model is based on a modification of the basic CCR model, where Banker et al. (1984) add the concept of variable scale performances to the concepts of PTE and SE. The BCC linear programming model calculates the PTE, evaluating the efficiency of each $DMU_o$ (o = 1, ..., n), solving the following mathematical model.

Objective function:

$$\min_{\theta_B,\lambda} \theta_B \tag{10}$$

Subject to:

$$\theta_B x_o - X\lambda \leq 0 \tag{11}$$



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We use a variation of the production approach, where outputs are related to the bank's activity, while the inputs are the resources needed

$$X\lambda \leq x_0 \tag{12}$$

$$e\lambda = 1 \tag{13}$$

$$\lambda \geq 0 \tag{14}$$

Where $\theta_B$ is a scale measurement.

## 2.3. Description of the variables

There is currently discussion in the banking literature regarding the correct definition of data inputs and outputs. Berger and Humphrey (1997) identify two main approaches for the selection of inputs and outputs; they are the "production approach" and the "intermediation approach". The first assumes that banks make loans and deposits, and in doing so, they use inputs such as work and capital, and the number and type of transactions or documents are processed as output variables. The second approach considers banks as intermediaries between the savers and the investors. These same authors allege that neither of these approaches is perfect, because they do not fully capture the essence of the function of financial institutions as providers of transactions. In fact, different studies have indicated that the focus on intermediation may be better for evaluating the efficiency of bank branches and the focus on production might be more appropriate for evaluating the financial institutions as a whole. Support for both approaches can be found in the literature; however, we used a variation on the production approach, where the outputs are related to the banking activity, while the inputs are the resources necessary to carry out said activities.

Based on the observations made by Berger and Humphrey (1997), previous studies (Isik & Hassan, 2002; Casu & Molyneux, 2003; Tsionas, Lolos & Christopoulos, 2003; Havrylchyk, 2006; Sealey & Lindley, 1977; Tortosa-Ausina, 2002) and the structure of the database used (Bank Superintendency of Ecuador), the following variables were considered in the models that were developed:

• *Inputs:* Fixed Assets (FA), Operating Expenses (OE)
• *Outputs:* Accounts Receivable (AR), Income (INC), Investments (INV), Total Deposits (TD)

A sensitivity analysis has also been carried out, taking into account the intermediation approach, i.e., the TD variable is considered as an input, while the accounts receivable and investment variables continue to be outputs. The results will be presented further on.

## 2.4. Description of the data

The information corresponding to each of the variables was taken from the annual financial information bulletins published on the website of the Bank Superintendency, the supervisory body that publishes information corresponding to the accounting periods of each of the financial institutions on a monthly basis.

All banks have been considered for the analysis, of which those were filtered that remained during all periods of analysis (1993-1999 and 2000-2018). An efficiency analysis will subsequently be conducted only on those banks that survived the banking crisis of 1999 and 2000.



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**This analysis considers all banks, from which those that remain operative throughout all the analysis periods have been filtered**

The data on the DMUs were taken from the reports corresponding to December of each year during the period of analysis. Table 1 indicates the list of banking institutions considered in the study during the 1993-1999 period, organized into the given categories according to the size of each institution. This categorization is established according to the percentile method applied to total assets. Table 2 presents the list of banking institutions studied during the 2000-2018 period, categorized according to the same criteria (Bank Superintendency, 2017). It should be mentioned that fewer banks are analyzed in the second period as the result of the strong impact of the financial crisis the country suffered during 1999 and 2000.

Table 1
### List of financial institutions considered in the analysis period 1993-1999

| Name of the financial institution | Abbreviation | Assets (Dec. 1999) in millions of sucres |
|---|---|---|
| **Large banks** | | |
| FILANBANCO | DMU1 | 16,047,672.53 |
| PICHINCHA | DMU2 | 11,898,689.60 |
| DE GUAYAQUIL | DMU3 | 8,557,816.40 |
| PACIFICO | DMU4 | 7,728,270.47 |
| PROGRESO | DMU5 | 7,103,514.18 |
| POPULAR | DMU6 | 6,680,903.19 |
| PRODUBANCO | DMU7 | 5,645,355.89 |
| PREVISORA | DMU8 | 4,721,717.85 |
| CONTINENTAL | DMU9 | 3,651,780.61 |
| CITIBANK | DMU10 | 3,513,307.69 |
| BOLIVARIANO | DMU11 | 2,917,554.52 |
| PRESTAMOS | DMU12 | 2,381,382.84 |
| **Medium-sized banks** | | |
| INTERNACIONAL | DMU13 | 1,976,568.93 |
| AUSTRO | DMU14 | 1,431,094.05 |
| LLOYDS | DMU15 | 1,339,753.42 |
| TUNGURAHUA | DMU16 | 1,204,680.64 |
| GRAL. RUMIÑAHUI | DMU17 | 933,108.45 |
| AMAZONAS | DMU18 | 901,507.53 |
| MACHALA | DMU19 | 870,109.98 |
| CREDITO | DMU20 | 801,524.77 |
| **Small banks** | | |
| AZUAY | DMU21 | 742,354.55 |
| LOJA | DMU22 | 291,758.73 |
| LITORAL | DMU23 | 201,580.46 |
| TERRITORIAL | DMU24 | 174,337.66 |

Source: Bank Superintendency, 2019.
Compiled by the Authors.

There is a reduced number of banks analyzed in the second period, due to the strong impact of the financial crisis

Table 2
**List of financial institutions considered in the analysis period 2000-2018**

| Name of the financial institution | Abbreviation | Assets (Dec. 2018) in thousands of USD |
|---|---|---|
| **Large banks** | | |
| BP PICHINCHA | DMU2 | 10,615,390.88 |
| BP PACIFICO | DMU4 | 5,451,933.88 |
| BP PRODUBANCO | DMU7 | 4,271,783.49 |
| BP GUAYAQUIL | DMU3 | 4,023,542.09 |
| **Medium-sized banks** | | |
| BP INTERNACIONAL | DMU13 | 3,558,412.08 |
| BP BOLIVARIANO | DMU11 | 3,114,918.93 |
| BP AUSTRO | DMU14 | 1,692,870.79 |
| BP GENERAL RUMIÑAHUI | DMU17 | 829,859.26 |
| BP SOLIDARIO | DMU25 | 720,162.20 |
| BP MACHALA | DMU19 | 698,383.71 |
| BP CITIBANK | DMU10 | 642,798.01 |
| BP LOJA | DMU22 | 446,942.85 |
| **Small banks** | | |
| BP AMAZONAS | DMU18 | 165,431.22 |
| BP COMERCIAL DE MANABI | DMU26 | 57,167.05 |
| BP LITORAL | DMU23 | 37,496.83 |

Source: Bank Superintendency, 2019.
Compiled by the Authors.

## 3. Results

Tables 3, 4, 5 and 6 present the efficiency ratios obtained in the CCR and BCC analysis models focused on inputs during the two periods of analysis.

Tables 3 and 5 show the efficiency ratios obtained by applying the CCR model for banks during the periods 1992-1999 and 2000-2018, respectively, while Tables 4 and 6 show the ratios with the application of the BCC model for the same periods.

Table 3 indicates that according to the CCR approach in the large bank category, there is only 1 DMU that is completely efficient during the period of analysis, while in medium-sized and small banks, no DMU reached full efficiency in all periods. However, on average, medium-sized banks demonstrate a greater level of efficiency, followed by small banks; meanwhile, large banks present the lowest level of efficiency. Using this same approach, in Table 5 it can be seen that during the period 2000-2018, exclusively in the medium-sized bank category, there was one single DMU that was shown to be completely efficient during the period of analysis, while in the large and small bank categories there were no institutions that reached efficiency in all periods. However, unlike the previous period of analysis, in this period the average for superior efficiency is reached in large banks at rate of 98.72%, followed by medium-sized and small banks, with rates of 97.24% and 90.32%, respectively.



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**During the period 2000-2018, exclusively in the medium-sized bank category, one single DMU is completely efficient**

Table 3
**Efficiency ratios from the CCR-I model during the 1993-1999 period**

| DMU | 1993 | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 |
|---|---|---|---|---|---|---|---|
| Large banks | | | | | | | |
| DMU1 | 0.45 | 0.76 | 0.71 | 0.97 | 1 | 1 | 1 |
| DMU2 | 0.49 | 0.65 | 0.61 | 0.84 | 1 | 0.77 | 0.67 |
| DMU3 | 0.80 | 1 | 1 | 1 | 0.60 | 1 | 0.96 |
| DMU4 | 0.41 | 0.45 | 0.64 | 0.98 | 0.33 | 0.70 | 0.37 |
| DMU5 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| DMU6 | 0.41 | 0.72 | 0.69 | 0.94 | 0.71 | 0.60 | 0.17 |
| DMU7 | 0.69 | 0.63 | 0.51 | 0.70 | 0.51 | 0.64 | 0.85 |
| DMU8 | 0.38 | 0.36 | 0.41 | 0.78 | 0.54 | 0.70 | 1 |
| DMU9 | 0.34 | 0.57 | 1 | 0.29 | 0.28 | 0.52 | 0.76 |
| DMU10 | 0.58 | 1 | 1 | 1 | 1 | 1 | 1 |
| DMU11 | 0.21 | 0.41 | 0.47 | 0.44 | 0.41 | 0.71 | 0.79 |
| DMU12 | 0.27 | 0.52 | 0.89 | 1 | 1 | 1 | 1 |
| **Mean** | **0.50** | **0.67** | **0.74** | **0.83** | **0.70** | **0.80** | **0.80** |
| Medium-sized banks | | | | | | | |
| DMU13 | 0.42 | 0.50 | 0.36 | 0.75 | 0.56 | 0.74 | 0.70 |
| DMU11 | 0.63 | 0.71 | 0.99 | 1 | 1 | 1 | 1 |
| DMU14 | 1 | 1 | 1 | 0.68 | 1 | 1 | 1 |
| DMU17 | 1 | 1 | 1 | 0.64 | 0.63 | 0.44 | 0.75 |
| DMU25 | 1 | 0.84 | 1 | 1 | 1 | 0.84 | 1 |
| DMU19 | 0.38 | 0.52 | 0.92 | 0.90 | 0.54 | 0.62 | 0.49 |
| DMU10 | 0.27 | 0.33 | 0.39 | 0.57 | 0.55 | 0.75 | 0.69 |
| DMU22 | 1 | 0.67 | 0.93 | 0.54 | 0.86 | 1 | 1 |
| **Mean** | **0.71** | **0.70** | **0.83** | **0.76** | **0.77** | **0.80** | **0.83** |
| Small banks | | | | | | | |
| DMU21 | 0.40 | 0.51 | 0.64 | 0.67 | 0.76 | 0.96 | 0.04 |
| DMU22 | 1 | 0.85 | 0.89 | 1 | 0.57 | 0.44 | 0.36 |
| DMU23 | 1 | 1 | 1 | 0.87 | 0.78 | 0.74 | 1 |
| DMU24 | 0.28 | 0.97 | 0.46 | 0.95 | 1 | 0.93 | 0.60 |
| **Mean** | **0.67** | **0.83** | **0.75** | **0.87** | **0.78** | 0.77 | 0.50 |

Table 4, according to the BCC approach, indicates that during the period 1993-1999, there were three large banks that attained efficiency in every period, but only one is the same as in the CCR model (DMU5). In turn, according to this approach in the small bank category, there is also one institution that is completely efficient in every period, a situation that does not occur with the previous approach. Similarly, the average efficiencies are higher with the BCC approach as opposed to the CCR approach, even though they do not maintain the same trend. With the BCC approach, small banks are on average more efficient (84.75%), followed by large banks (82.57%) and finally medium-sized banks (79.18%). On the other hand, Table 6 shows

**According to the BCC approach, in the period 1993-1999, there were three large banks that achieved efficiency in all periods**

that in both the large and small bank categories, there are 2 institutions that are efficient in all periods. The levels of efficiency are higher on average as compared to the CCR approach, with large banks reaching the highest level of efficiency (98.78%), followed by small banks (98.46%) and finally, medium-sized banks (93.79%). It can also be seen that between the years 2002 and 2014, large banks present perfect efficiencies, while banks in the small category have perfect efficiencies for the periods 2001, 2002, 2006-2011, 2013 and 2016.

Table 4

### Efficiency ratios from the BCC-I model during the 1993-1999 period

| DMU | 1993 | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 |
|---|---|---|---|---|---|---|---|
| Large banks | | | | | | | |
| DMU1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| DMU2 | 1 | 1 | 1 | 1 | 1 | 1 | 0.90 |
| DMU3 | 1 | 1 | 1 | 1 | 0.61 | 1 | 1 |
| DMU4 | 1 | 1 | 1 | 1 | 0.33 | 0.7 | 0.41 |
| DMU5 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| DMU6 | 0.65 | 1 | 1 | 1 | 1 | 0.81 | 0.86 |
| DMU7 | 0.85 | 0.66 | 0.51 | 0.76 | 0.57 | 0.64 | 1 |
| DMU8 | 0.40 | 0.38 | 0.41 | 0.78 | 0.54 | 0.71 | 1 |
| DMU9 | 0.90 | 0.78 | 1 | 0.30 | 0.28 | 0.53 | 0.78 |
| DMU10 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| DMU11 | 0.21 | 0.42 | 0.48 | 0.44 | 0.41 | 0.72 | 0.91 |
| DMU12 | 0.27 | 0.53 | 0.89 | 1 | 1 | 1 | 1 |
| **Mean** | **0.77** | **0.81** | **0.86** | **0.86** | **0.73** | **0.84** | **0.91** |
| Medium-sized banks | | | | | | | |
| DMU13 | 0.42 | 0.56 | 0.37 | 0.78 | 0.56 | 0.77 | 0.76 |
| DMU11 | 0.64 | 0.72 | 1 | 1 | 1 | 1 | 1 |
| DMU14 | 1 | 1 | 1 | 0.79 | 1 | 1 | 1 |
| DMU17 | 1 | 1 | 1 | 0.67 | 0.66 | 0.45 | 0.88 |
| DMU25 | 1 | 0.91 | 1 | 1 | 1 | 0.88 | 1 |
| DMU19 | 0.45 | 0.55 | 0.94 | 0.92 | 0.56 | 0.66 | 0.51 |
| DMU10 | 0.27 | 0.41 | 0.41 | 0.58 | 0.56 | 0.77 | 0.71 |
| DMU22 | 1 | 0.67 | 1 | 0.55 | 1 | 1 | 1 |
| **Mean** | **0.72** | **0.73** | **0.84** | **0.79** | **0.79** | **0.82** | **0.86** |
| Small banks | | | | | | | |
| DMU21 | 0.41 | 0.59 | 0.68 | 0.72 | 0.86 | 1 | 0.06 |
| DMU22 | 1 | 1 | 1 | 1 | 0.66 | 0.51 | 0.54 |
| DMU23 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| DMU24 | 0.70 | 1 | 1 | 1 | 1 | 1 | 1 |
| **Mean** | **0.78** | **0.90** | **0.92** | **0.93** | **0.88** | **0.88** | **0.65** |

Table 5

## Efficiency ratios from the CCR-I model during the 2000-2018 period

| DMU | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Large banks** | | | | | | | | | | | | | | | | | | | |
| DMU2 | 1 | 1 | 0.73 | 0.82 | 0.99 | 0.87 | 0.9 | 0.87 | 0.93 | 0.94 | 0.94 | 0.98 | 1 | 0.84 | 0.96 | 0.78 | 1 | 0.94 | 0.84 |
| DMU4 | 0.49 | 0.68 | 0.85 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0.96 | 1 | 1 | 1 |
| DMU7 | 0.99 | 0.85 | 0.79 | 0.92 | 1 | 0.93 | 1 | 1 | 1 | 1 | 1 | 0.93 | 0.95 | 0.91 | 0.95 | 1 | 0.89 | 0.84 | 0.88 |
| DMU3 | 0.83 | 1 | 1 | 1 | 0.94 | 1 | 1 | 0.97 | 1 | 1 | 1 | 1 | 0.89 | 0.93 | 1 | 0.8 | 0.82 | 0.85 | 0.92 |
| **Mean** | **0.83** | **0.88** | **0.84** | **0.94** | **0.98** | **0.95** | **0.97** | **0.96** | **0.98** | **0.98** | **0.98** | **0.98** | **0.96** | **0.92** | **0.98** | **0.89** | **0.93** | **0.91** | **0.91** |
| **Medium-sized banks** | | | | | | | | | | | | | | | | | | | |
| DMU13 | 1 | 0.88 | 1 | 0.92 | 0.91 | 0.96 | 0.93 | 0.83 | 0.94 | 0.95 | 0.99 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| DMU11 | 0.82 | 0.98 | 0.95 | 0.86 | 0.94 | 1 | 1 | 1 | 1 | 0.95 | 1 | 1 | 0.99 | 0.95 | 1 | 1 | 0.89 | 0.97 | 0.91 |
| DMU14 | 1 | 1 | 0.82 | 0.88 | 0.91 | 0.83 | 0.72 | 0.88 | 0.95 | 0.9 | 1 | 1 | 0.93 | 1 | 1 | 0.92 | 0.91 | 1 | 1 |
| DMU17 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0.94 | 1 | 1 | 0.97 | 0.92 | 1 |
| DMU25 | 0.5 | 0.84 | 0.73 | 0.9 | 1 | 1 | 1 | 0.63 | 0.94 | 1 | 1 | 1 | 1 | 1 | 0.91 | 0.92 | 1 | 1 | 1 |
| DMU19 | 0.51 | 0.59 | 0.71 | 0.78 | 0.73 | 0.7 | 0.64 | 0.5 | 0.59 | 0.62 | 0.65 | 0.64 | 0.67 | 0.67 | 0.66 | 0.62 | 0.64 | 0.66 | 0.73 |
| DMU10 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| DMU22 | 0.76 | 1 | 1 | 1 | 1 | 1 | 1 | 0.94 | 1 | 1 | 1 | 1 | 1 | 0.99 | 0.93 | 0.93 | 0.94 | 0.91 | 0.9 |
| **Mean** | **0.82** | **0.91** | **0.9** | **0.92** | **0.94** | **0.94** | **0.91** | **0.85** | **0.93** | **0.93** | **0.96** | **0.96** | **0.95** | **0.94** | **0.94** | **0.92** | **0.92** | **0.93** | **0.94** |
| **Small banks** | | | | | | | | | | | | | | | | | | | |
| DMU18 | 0.74 | 1 | 1 | 0.8 | 0.98 | 0.92 | 1 | 1 | 0.98 | 1 | 1 | 0.98 | 0.77 | 1 | 0.76 | 0.79 | 1 | 0.77 | 1 |
| DMU26 | 1 | 0.83 | 0.66 | 0.8 | 0.96 | 0.97 | 0.86 | 0.84 | 0.7 | 0.65 | 0.57 | 0.58 | 0.8 | 1 | 0.68 | 0.7 | 0.79 | 0.91 | 0.64 |
| DMU23 | 1 | 1 | 1 | 1 | 1 | 1 | 0.98 | 1 | 0.77 | 1 | 1 | 0.99 | 0.64 | 0.57 | 0.63 | 0.77 | 0.67 | 0.63 | 0.72 |
| **Mean** | 0.91 | 0.94 | 0.89 | 0.86 | 0.98 | 0.96 | 0.94 | 0.95 | 0.82 | 0.88 | 0.86 | 0.85 | 0.74 | 0.86 | 0.69 | 0.75 | 0.82 | 0.77 | 0.79 |

Table 6

## Efficiency ratios from the BCC-I model during the 2000-2018 period

| DMU | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Large banks** | | | | | | | | | | | | | | | | | | | |
| DMU2 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| **DMU4** | 1 | 0.68 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| **DMU7** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| **DMU3** | 0.84 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0.85 | 0.87 | 0.9 | 0.94 |
| **Mean** | **0.96** | **0.92** | **1** | **1** | **1** | **1** | **1** | **1** | **1** | **1** | **1** | **1** | **1** | **1** | **1** | **0.96** | **0.97** | **0.98** | **0.98** |
| **Medium-sized banks** | | | | | | | | | | | | | | | | | | | |
| **DMU13** | 1 | 1 | 1 | 0.97 | 0.99 | 1 | 0.94 | 0.84 | 0.97 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| **DMU11** | 0.87 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0.97 | 0.97 | 0.93 |
| **DMU14** | 1 | 1 | 0.92 | 0.9 | 0.94 | 0.85 | 0.75 | 0.88 | 0.95 | 0.95 | 1 | 1 | 0.94 | 1 | 1 | 0.92 | 0.92 | 1 | 1 |
| **DMU17** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0.99 | 1 | 1 | 0.98 | 1 | 1 |
| **DMU25** | 0.56 | 0.85 | 0.97 | 1 | 1 | 1 | 1 | 0.64 | 0.95 | 1 | 1 | 1 | 1 | 1 | 0.95 | 0.96 | 1 | 1 | 1 |
| **DMU19** | 0.52 | 0.60 | 0.71 | 0.82 | 0.76 | 0.73 | 0.65 | 0.52 | 0.59 | 0.62 | 0.65 | 0.65 | 0.7 | 0.68 | 0.68 | 0.64 | 0.67 | 0.69 | 0.78 |
| **DMU10** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| **DMU22** | 0.78 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0.98 | 0.98 | 0.99 | 0.97 | 0.94 |
| **Mean** | **0.84** | **0.93** | **0.95** | **0.96** | **0.96** | **0.95** | **0.92** | **0.86** | **0.93** | **0.95** | **0.96** | **0.96** | **0.96** | **0.96** | **0.95** | **0.94** | **0.94** | **0.95** | **0.96** |
| **Small banks** | | | | | | | | | | | | | | | | | | | |
| **DMU18** | 0.8 | 1 | 1 | 0.83 | 0.99 | 0.95 | 1 | 1 | 1 | 1 | 1 | 1 | 0.87 | 1 | 0.89 | 0.9 | 1 | 0.9 | 1 |
| **DMU26** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| **DMU23** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| **Mean** | **0.93** | **1** | **1** | **0.94** | **1** | **0.98** | **1** | **1** | **1** | **1** | **1** | **1** | **0.96** | **1** | **0.96** | **0.97** | **1** | **0.97** | **1** |

**In 1999, one bank reached the lowest efficiency level of the entire analysis period, of approximately 4.31%**

Tables 7 and 8 show the results obtained from the analysis of the descriptive statistics for each model. Table 7 shows that both the CCR and the BCC measurements show minimum efficiency averages in the year 1993, with 60.07% and 75.68%, respectively. However, in 1999 there is one bank that reaches its lowest efficiency for the entire period of analysis, equal to approximately 4.31% (this bank would later cease activity in the following years). Table 8 demonstrates that the year with the lowest efficiencies is 2000, both in terms of the average and minimum values; this is also the year with the highest standard deviations, which provides significant evidence of the disparity in terms of the variation in efficiency among the different banks.

Table7

**Descriptive statistics for the efficiency ratios during the period 1993-1999**

| CCR 93-99 | 1993 | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 |
|---|---|---|---|---|---|---|---|
| Average | 0.60 | 0.71 | 0.77 | 0.81 | 0.73 | 0.80 | 0.76 |
| Max | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Min | 0.21 | 0.33 | 0.36 | 0.29 | 0.28 | 0.44 | 0.04 |
| St Dev | 0.29 | 0.23 | 0.24 | 0.21 | 0.25 | 0.19 | 0.29 |
| BCC 93-99 | 1993 | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 |
| Average | 0.76 | 0.80 | 0.86 | 0.85 | 0.78 | 0.84 | 0.85 |
| Max | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Min | 0.21 | 0.38 | 0.37 | 0.30 | 0.28 | 0.45 | 0.06 |
| St Dev | 0.29 | 0.23 | 0.23 | 0.21 | 0.25 | 0.19 | 0.24 |

Table 8

**Descriptive statistics for the efficiency ratios during the period 2000-2018**

| CCR-I (00-18) | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Average** | 0.84 | 0.91 | 0.88 | 0.91 | 0.96 | 0.95 | 0.93 | 0.90 | 0.92 | 0.93 | 0.94 | 0.94 | 0.91 | 0.92 | 0.90 | 0.88 | 0.90 | 0.89 | 0.90 |
| **Max** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| **Min** | 0.49 | 0.59 | 0.66 | 0.78 | 0.73 | 0.70 | 0.64 | 0.50 | 0.59 | 0.62 | 0.57 | 0.58 | 0.64 | 0.57 | 0.63 | 0.62 | 0.64 | 0.63 | 0.64 |
| **St Dev** | 0.20 | 0.13 | 0.13 | 0.09 | 0.07 | 0.09 | 0.11 | 0.15 | 0.13 | 0.13 | 0.14 | 0.14 | 0.13 | 0.13 | 0.14 | 0.13 | 0.12 | 0.12 | 0.12 |
| **BCC-I (00-18)** | **2000** | **2001** | **2002** | **2003** | **2004** | **2005** | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** | **2012** | **2013** | **2014** | **2015** | **2016** | **2017** | **2018** |
| **Average** | 0.89 | 0.94 | 0.97 | 0.97 | 0.98 | 0.97 | 0.96 | 0.93 | 0.96 | 0.97 | 0.98 | 0.98 | 0.97 | 0.98 | 0.97 | 0.95 | 0.96 | 0.96 | 0.97 |
| **Max** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| **Min** | 0.52 | 0.60 | 0.71 | 0.82 | 0.76 | 0.73 | 0.65 | 0.52 | 0.59 | 0.62 | 0.65 | 0.65 | 0.70 | 0.68 | 0.68 | 0.64 | 0.67 | 0.69 | 0.78 |
| **St Dev** | 0.16 | 0.13 | 0.07 | 0.06 | 0.06 | 0.08 | 0.11 | 0.15 | 0.11 | 0.10 | 0.09 | 0.09 | 0.08 | 0.08 | 0.08 | 0.10 | 0.09 | 0.08 | 0.06 |

## 4. Sensitivity Analysis

Table 9 shows the results of a sensitivity analysis in which the intermediation approach is applied. The main difference between the model proposed in the present work and this new focus lies in the TD (Total Deposit) variable, which was considered to be an output, but is now considered to be an input variable.



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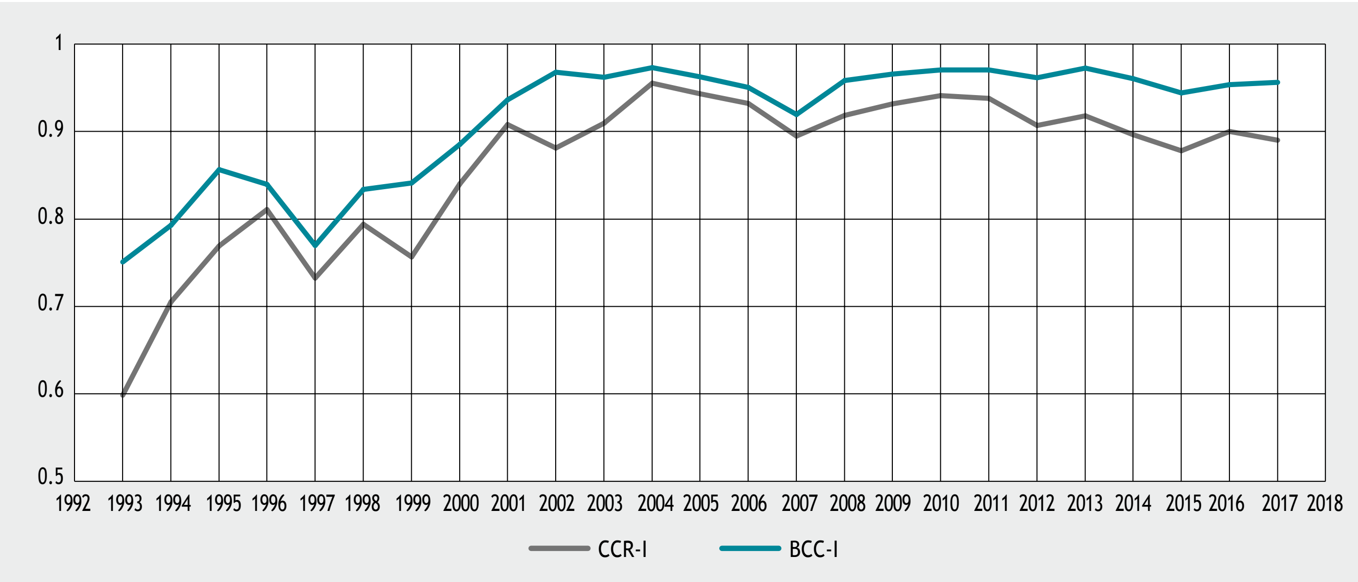
**The intermediation approach evidences a notable reduction in the level of efficiency as compared to the production approach**

Table 9
**Efficiency ratios from the intermediation approach during the 1993-2018 period**

| Year | CCR-I | BCC-I | Year | CCR-I | BCC-I | Year | CCR-I | BCC-I |
|---|---|---|---|---|---|---|---|---|
| 1993 | 47.84% | 79.01% | 2003 | 92.77% | 95.67% | 2013 | 95.48% | 97.74% |
| 1994 | 84.95% | 90.85% | 2004 | 95.93% | 96.69% | 2014 | 96.40% | 98.00% |
| 1995 | 82.70% | 89.91% | 2005 | 92.00% | 95.26% | 2015 | 96.27% | 97.80% |
| 1996 | 80.84% | 86.00% | 2006 | 94.55% | 95.76% | 2016 | 92.73% | 96.48% |
| 1997 | 73.16% | 79.57% | 2007 | 95.36% | 96.26% | 2017 | 96.17% | 96.21% |
| 1998 | 71.84% | 80.46% | 2008 | 92.79% | 96.22% | 2018 | 93.61% | 97.85% |
| 1999 | 74.38% | 82.86% | 2009 | 93.44% | 97.11% | | | |
| 2000 | 74.10% | 86.75% | 2010 | 93.41% | 97.17% | | | |
| 2001 | 93.62% | 96.47% | 2011 | 94.42% | 97.38% | | | |
| 2002 | 84.41% | 96.15% | 2012 | 95.51% | 96.80% | | | |

As in the previous tables, the trend toward the BCC approach presenting a higher efficiency than the CCR approach is maintained. However, there is evidence of a noticeable reduction in the level of efficiency as compared to the production approach presented in the methodology. These results can lead us to understand that the banking activity is not as efficient when analyzing the acquisition and placement of resources in the market. It is also necessary to mention that the lowest efficiency appears in 1993 (47.84%), while the highest occurs in 2014 (96.40%), both results according to the CCR approach. According to the BCC approach, the lowest and highest efficiencies are found in the aforementioned years, but the percentages increase to 79.01% and 98%, respectively.

Figure 1
**Fluctuation in the average levels of efficiency during the period 1992-2018**



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**The year of analysis with the lowest level of efficiency is 1993, however, there are decreases in efficiency levels in 1997, 1999, 2007 and 2015**

Figure 1 shows the evolution of the average efficiency ratios in the banking sector, where it can be seen that in a general sense, the performance of the decision-making units is higher in the BCC model. It can also be seen that the year of analysis with the lowest level of efficiency is 1993; however, in 1997, 1999, 2007 and 2015 decreases in efficiency levels also occurred, a trend that is revealed by both models. The highest moments of efficiency occurred during the periods 2004 and 2013, and on the other hand, according to the BCC approach, during the period 2008-2014, apparent stability is observed in the efficiency levels, while the CCR model shows no such stability.

In a complementary manner, national and international banking regulations and the studies conducted allow us to define situations or factors that can explain the levels of efficiency found in the analyzed periods (Coca Valle, 2015; Lucas Pérez & Salcedo López, 2004).

In addition, the efficiency of the banking sector has been evaluated analyzing only those banks that remained in operation throughout the entire period of analysis (1993-2018), in other words, those that survived the banking crisis that affected the country in the years 1999 and 2000. The results can be seen in Table 10, which shows the BCC and CCR approaches. As mentioned throughout the document, the BCC approach shows higher levels of efficiency than the CCR approach.

Table 10
**Efficiency ratios for 1993-2018, considering banks that survived the financial crisis**

| Year | BCC | CCR | Year | BCC | CCR |
|---|---|---|---|---|---|
| 1993 | 91.04% | 65.83% | 2006 | 95.61% | 95.04% |
| 1994 | 95.26% | 92.97% | 2007 | 96.57% | 95.22% |
| 1995 | 88.43% | 82.67% | 2008 | 96.51% | 95.77% |
| 1996 | 84.60% | 81.69% | 2009 | 96.66% | 96.50% |
| 1997 | 82.50% | 76.05% | 2010 | 97.17% | 96.79% |
| 1998 | 90.48% | 80.18% | 2011 | 97.11% | 96.62% |
| 1999 | 90.86% | 80.18% | 2012 | 97.70% | 96.28% |
| 2000 | 87.64% | 77.26% | 2013 | 97.74% | 96.07% |
| 2001 | 96.11% | 94.11% | 2014 | 98.12% | 97.55% |
| 2002 | 95.57% | 83.31% | 2015 | 97.84% | 97.16% |
| 2003 | 96.55% | 94.54% | 2016 | 97.09% | 93.96% |
| 2004 | 96.29% | 95.39% | 2017 | 97.48% | 95.48% |
| 2005 | 96.67% | 92.95% | 2018 | 97.57% | 95.39% |

In order to compare the results obtained by analyzing all the banks that operated in each period and those that maintained operations during the years 1993 and 2018, a summary table has been created, showing the most significant variations. In most years, a higher level of efficiency can be seen when analyzing only the banks that survived the crisis period, while in other years there are no noticeable differences.



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**It should be noted that in the 1993-1999 period, when the banks that were dissolved between 1999 and 2000 are not considered, efficiency increases by as much as 22%**

Table 11 shows these differences. It should be stressed that during the period 1993-1999, if the banks that disappeared between 1999 and 2000 are not considered, the efficiency increases to 22%, depending on the approach used (CCR); in other words, the banks that did not manage to overcome the impasse of the bank holiday reduced the efficiency of the sector during this period, by 15% and 22%, depending on the year.

However, during the early years of the 2000-2018 period, efficiency improved by as much as 5%, thanks to the emergence of new banks that were founded after the banking crisis. However, in the latest periods analyzed, it can be seen once again that the banks that survived the crisis are the ones that increase in efficiency, even though they do so with low percentages.

Table 11
**Difference in efficiency ratios for 1993-2018, considering banks that survived the financial crisis**

| Year | BCC | CCR | Year | BCC | CCR |
|---|---|---|---|---|---|
| 1993 | 15% | 6% | 2006 | 0% | 1% |
| 1994 | 15% | 22% | 2007 | 4% | 5% |
| 1995 | 2% | 6% | 2008 | 1% | 4% |
| 1996 | 0% | 1% | 2009 | 0% | 3% |
| 1997 | 4% | 3% | 2010 | –1% | 3% |
| 1998 | 6% | 0% | 2011 | –1% | 3% |
| 1999 | 6% | 4% | 2012 | 1% | 5% |
| 2000 | –1% | –7% | 2013 | 0% | 4% |
| 2001 | 2% | 3% | 2014 | 1% | 8% |
| 2002 | –1% | –5% | 2015 | 3% | 9% |
| 2003 | 0% | 4% | 2016 | 1% | 4% |
| 2004 | –2% | –1% | 2017 | 1% | 6% |
| 2005 | 0% | –2% | 2018 | 1% | 5% |

## 5. Conclusions and discussion

Using the DEA method of non-parametric data analysis, we were able to measure the efficiency of banking institutions in Ecuador, considering two periods of analysis: 1993-1999 and 2000-2018. The cut-off date was set in 1999 to analyze the behavior of Ecuadorian banking before and after the bank holiday (currency substitution), considering it to be one of the most important financial events in the Ecuadorian economy, which caused several negative effects, one of the most important of which was the closure of several financial institutions. This event even led to the change in currency, adopting a "borrowed" currency (the U.S. dollar) in 2000, which would limit and even prevent the state from taking action in establishing monetary policies.

This analysis provides relevant information about the performance of the analysis units. It is important to stress that there are differences between the analyses according to the CCR and BCC approaches.

**This event even led to the substitution of the national currency, with the adoption of a “borrowed” currency (USD) in 2000, which limits the state’s action in establishing monetary policies**

During the period 1993-1999, a total of 24 financial institutions were analyzed and classified according to the amount of their assets as large, medium-sized or small banks. On the other hand, during the period 2000-2018, only 15 units were analyzed. The difference in units analyzed is explained by the closure of institutions following the 1999 crisis.

After 2000, a relative stability occurred in efficiency levels, with the exception of the year 2007, when a decrease in the ratios is observed, but one that never reaches the levels of the 1993-1999 period. This answers the first and second research questions, confirming that the efficiency of Ecuadorian banks has been higher following the adoption of the dollar as the national currency.

There is one financial institution that has been fully efficient in both periods of analysis according to the BCC approach: DMU 10, which corresponds to City Bank, a foreign private bank.

During the period 2000-2018, large banks obtained on average a higher level of efficiency. There were even years in which the efficiency in this segment reached values of nearly 100%, which answers the third research question. The ratios differ slightly, depending on the approach used. The evidence shows that with the BCC model, they are higher, due to the mathematical considerations involved, which cause the difference between the ratio obtained for each DMU and the efficiency frontier to be less than that resulting from the CCR approach.

With regard to the fourth research question, those DMUs that are not fully efficient are recommended to make an effort to adjust the variables analyzed to improve their levels of efficiency. However, the limitations to resources often prevent adjusting all the variables at the same time, so we recommend placing greater emphasis on the input variables, i.e., fixed assets and operating expenses.

Finally, the levels of efficiency obtained in each period can be explained as follows: in the period 1993-1999, the low ratios could be related to the publication of the General Financial System Institution Act passed on May 12, 1994, which failed to explain in sufficient detail the meaning of “financial groups,” thus permitting shareholders in private financial institutions to own companies to which they could grant credit funds known as “related loans.” Furthermore, in 1997, more than half (55%) of the “signature loans” provided by the financial system had no guarantee to ensure their recovery; however, the ratio between loans and fund acquisition reached approximately 99%, which did not permit customer deposits to be recovered if necessary.

In addition, another factor that could have had an influence are the aggressive natural phenomena that occurred in the late 1990s, the “El Niño Phenomenon,” which brought about great losses in the production sector and a decrease in the GDP. In 1999, in light of the lack of assistance from the Ecuadorian financial system, the little money that was found in the banks was withdrawn by those who decided to start small businesses, taking advantage of economic reactivation programs, which left the banks severely under-financed.

With regard to the period 2000-2018, the higher levels of efficiency may be the result of the implementation of consolidation programs in the financial sector, developed within the regulatory framework of the Basel Rules, which were intended to increase the internal control over financial institutions, ensuring adequate risk management by establishing Banking Board resolutions and the control and monitoring by the Bank Superintendency.

**With regard to the 2000-2018 period, higher efficiency levels may be a consequence of the implementation of programs to strengthen the financial sector**

Another crucial factor for increasing efficiency is the development and incorporation of technologies in the banking system. According to Angulo (2019) y El Comercio (2019), the Ecuador Banking Association has focused its efforts on increasing the number of technological advances, such as ATMs and digital means, including applications for mobile telephones, telephone banking, virtual banking, etc., offering new services such as mobile payment and cash withdrawals from any ATM, among others, making it possible to improve activities through the optimization of resources, constituting more effective, efficient institutions.

DEA methodology has been successfully applied to institutions in the banking sector, and we have obtained a general overview of the past and present situation of these institutions in Ecuador. This will serve as a basis and theoretical framework for possible studies and research in the future, enabling better decisions to be made in both the public and private sector.

## 6. Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

## 7. Funding

This article had the academic endorsement and was supported by the Faculty of Economic and Administrative Sciences of Universidad de Cuenca.

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Harvard Deusto Business Research. Volume IX. Issue 1. Pages 20-39. ISSN: 2254-6235