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ORIGINAL RESEARCH ARTICLE

A comparative analysis of efficiency in the Brazilian banking sector: A data envelopment analysis approach

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ABSTRACT

This work aims to analyze the efficiency of Brazilian financial institutions until the COVID-19 pandemic period, from production and profitability perspectives. To accomplish this, the data envelopment analysis (DEA) techniques, specifically the CCR and BCC models, are applied to 213 Brazilian financial institutions in four methodological stages. The first step involved conducting a literature review of similar studies. The second step consisted of gathering financial information for each bank through the website of the Central Bank of Brazil. The third step involved selecting the variables to be used in the models. The fourth step was outlier detection using the jackstrap method. Subsequently, the mentioned efficiency models were applied, and the most efficient banks were identified based on each perspective. The results identified heterogeneous groups of efficient banks based on different market segments, with a focus on the efficiency of large banks and public banks when considering the production-oriented perspective. It is also observed that new digital banks are among the banks considered efficient. These findings are valuable for the scientific literature investigating the sustainability of financial institutions, as well as for decision-makers seeking to make more efficient investment allocations and for banking supervisory authorities in formulating risk regulatory policies.

Keywords: banking efficiency; DEA; production and profitability approach

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1. Introduction

The analysis of the importance of efficient financial institutions is fundamental to the proper functioning and development of an economy. Banks play a crucial role in the efficient allocation of financial resources, facilitating investment financing, access to credit, and risk management. Furthermore, banks that operate efficiently play an important role in reducing information asymmetries, aiming to provide transparency and trust to market participants.

According to Staub et al.[1], the development of the banking system and the increase in its efficiency are related to greater economic growth. In this sense, institutions with low levels of efficiency can become insolvent, causing losses to depositors and compromising the soundness of the financial system.

The main contribution to a bank's long-term strategy is the assessment of its activities from the perspective of performance and efficiency. A developed and efficiently functioning banking system facilitates the development of other spheres of business in the national economy and therefore influences the development of the entire country[2].

The concept of efficiency is related to measuring a product for a given entry-level, and this concept can be applied to banking operations. In this sense, an efficient bank reaches maximum production levels for a given input level, or one that can minimize the inputs used for a given output level[1]. When analyzing its real situation, a bank is trying to realistically assess its strengths and weaknesses in the areas of products, pricing, distribution, communication policy, management, organizational structure, etc.—the most appropriate combination of financial and non-financial indicators to be used in a more in-depth assessment[2].

Bank efficiency can be measured according to three main approaches: intermediation, production, and profitability. The intermediation approach is used to assess the efficiency of banks in intermediating resources between agents with surplus resources and other economic agents. The production approach analyzes the efficiency of banks in providing banking services, such as opening accounts, clearing checks, reporting, and others. The profitability approach, widely used in Brazil, considers the efficiency of banks in generating profit given their costs.

The studies by Staub et al.[1] indicate that public banks are more efficient than private banks, while Becker et al.[3] point out that state public banks had the lowest efficiency indices and federal public banks the highest. In this way, considering the importance of the banking system in the economy, studies on banking efficiency contribute to understanding the determinants of efficiency, analyzing the effects of new rules on bank efficiency, identifying good and bad management practices, and supporting public policy decisions[4]. Regarding Brazilian banks, Staub et al.[1] state that changes in average efficiency over time may indicate that such efficiency is influenced by macroeconomic and regulatory changes.

Thus, the research problem of this paper is to identify which Brazilian banks are considered efficient, with analyses from both the production and profitability perspectives, considering different sizes of banks and market segments. To accomplish this, this study focused on analyzing financial statement data from 213 financial institutions until 2019 using the data envelopment analysis (DEA) method, specifically the CCR and BCC models. This approach aimed to disregard the effects of the COVID-19 pandemic on economic activities as well as to be neutral regarding the effects of countercyclical monetary policies applied in the domestic and global economies. This fact allows for future replication of the efficiency study within the same institutions after the normalization of monetary policy in order to disregard exogenous shocks.

The justification for this work lies in the importance of bank efficiency as a fundamental instrument for bank supervision and the fact that a developed banking system is associated with greater economic growth of the national product[1]. Thus, bank efficiency is correlated with risk classification analysis, playing a crucial role in systemic stability[5], and the sustainability of financial institutions. The more efficient the banks are, the more sustainable they will be, Grmanová and Ivanová[2].

Although analyses of bank efficiency have been conducted in previous studies, like Carminati et al.[6], Carminati et al.[7], Damenu and Beaumont[8], Grmanová and Ivanová[2], Cava et al.[5], Kumar et al.[9], Munir and Manarvi[10], Saha et al.[11], Staub et al.[1], Boubaker and Ngo[12], Endri et al.[13], Rahman et al.[14], Ravi[15], Wu et al.[16], this study brings relevance to the research field by including a large number of new banks, including new digital banks (fintechs) that have gained strong prominence in the Brazilian banking scene in recent years.

The results identify heterogeneous groups of efficient banks due to the number of financial institutions, with emphasis on the efficiency of large banks and public banks when oriented towards production. Complementarily, the identification of some new digital banks (fintechs) among those banks considered efficient has also been verified. These bank efficiency findings, with the inclusion of these new players, are opportune for the scientific literature in the investigation of the sustainability of financial institutions, in the choice of agents that seek to make more efficient decisions in their investment allocations and for the banking authority in the formulation of regulatory policies.

In addition to this introduction, the work has four more sections, in which the second section presents a brief literature review on the subject, section three explains the database and methodology used, section four brings the results, and section five concludes.

2. Literature review

The seminal work that originated the DEA technique was carried out by Charnes et al.[17]. However, the method was further explored, and two main application models can be cited:[17], which considers constant returns to scale, and Banker et al.[18], which consider variable returns to scale.

In Becker et al.[3], DEA is a mathematical programming technique, originally proposed by Charnes et al.[17], which evaluates the relative efficiency of several homogeneous units. These homogeneous units are called decision units (decision-making units—DMUs) and must perform similar activities to make the comparisons.

According to Novickytė and Droždz[19], efficiency can be measured using a border approach, and these can be parametric and non-parametric. DEA is a non-parametric method, which means that no prior functional form is assumed for the boundary. In this way, it is technical efficiency with a focus on input levels relative to outputs of a sample of decision units (DMUs).

Thanassoulis[20] explains that the DEA technique was developed to compare the relative efficiency of units that perform similar functions to the resources used and products produced, such as banks, schools, and hospitals. DEA is a non-parametric test, which means it does not require statistical assumptions. Therefore, there is no functional form for the frontier, such as linear or exponential. It is built from data.

The national and international literature presents a multitude of studies concerning the analysis of efficiency related to banks using a DEA model (data envelopment analysis). In this sense, Grmanová and Ivanová[2] present a study on the analysis of the efficiency of banks in Slovakia, where a survey was carried out across 13 banks in May 2015 for performance analysis using the DEA methodology, with variable returns to scale, oriented towards input. The objective of the work was to analyze the efficiency of banks so that it is possible to discover which indicators are important for the efficient bank in terms of efficiency and sustainability.

In this work, Grmanová and Ivanová[2] used data compared in 2009 and 2013 with two inputs: i) liabilities to banks and ii) operating costs. And also two outputs: i) loans and advances to banks and customers and, ii) non-financial income. The authors observed that the three largest banks in the Slovak national banking market were efficient in both analyzed years. In this sense, the largest bank was efficient in all models. However, it cannot be confirmed that the three largest banks would have similar efficiency ratios in all models[2].

Another study regarding the efficiency of banks in the literature is Cava et al.[5] where the authors carried out empirical research intending to evaluate the efficiency of banks that operated in the Brazilian market in 2013. For this purpose, banks' efficiency was identified according to the production approach with the DEA model. This research contributed to the literature by exploring the relationship between efficiency and business segment, as well as the relationship between efficiency and risk classification.

The data used are from the Central Bank of Brazil (BACEN), with 110 banks. Three variables were selected as inputs: the number of employees, operating expenses (excluding interest), and fixed assets. The outputs were represented by two variables: total deposits and income unrelated to financial intermediation. The measurement of bank efficiency by Cava et al.[5] was evaluated using the DEA technique in the BCC model oriented to outputs/outputs. The reason for using the BCC model is that the banking sector allows for economies of scale, that is, there are gains related to the quantity of services produced by a bank.

The main results were that federal public banks and large banks are, on average, more efficient. Banks operating in foreign exchange and retail, as well as banks with high credit rates, also achieved high levels of efficiency. Efficient banks were more profitable, lending less money in proportion to their total assets. Results also indicated that large banks have the highest average score, suggesting that large banks are more efficient. A possible explanation would be the economies of scale achieved by large banks[5].

Similarly, Staub et al.[1] analyze, in parallel, the cost, technical, and allocative efficiency of Brazilian banks in the period from 2000 to 2007 using the DEA methodology with panel data and variable returns to scale. Thus, 3 inputs were used: personnel expenses, net operating expenses, and funding costs. As outputs, the following were used: deposits, loans (totals net of provisions), and investments. Staub et al.[1] classified banks by size (large (9), medium (10), small (39) and micro (36)), totaling 94 banks in the analysis, as the literature provides evidence that bank size may be important in explaining bank efficiency. The data were taken from the COSIF of the Central Bank of Brazil.

Using a panel data model, we tested whether bank classification is a significant variable in explaining bank efficiency. An efficient bank is therefore expected to be able to use fewer inputs, such as interest, capital, and labor expenditures, and produce more outputs, such as deposits, loans, and investments[1]. The results of Staub et al.[1], regarding the efficiency of microbanks, suggest that the niche market hypothesis is a plausible assumption, which may help explain the recent wave of mergers and acquisitions. Public banks are more cost-efficient than private banks. This may be due to: i) the number of state-owned banks has been reduced in recent years and only more efficient banks are left in the Brazilian banking system; and ii) public banks have very large public servant payroll accounts and therefore have an important advantage[1].

Staub et al.[1] point out that, therefore, the assessment of bank efficiency, by itself, can be an important tool for bank supervision. Furthermore, average bank efficiency varies over time and appears to respond to macroeconomic shocks or changes in financial regulation.

Novickytė and Droždz[19] conducted a study in Lithuania to assess bank efficiency using the DEA method and evaluate performance in a low-interest rate environment. The study employed five alternative models based on production, profitability, and intermediation dimensions, with varying input-output combinations. Their study encompassed multiple dimensions and employed various input-output combinations. The models incorporated inputs such as deposits, labor expenses, and debts and outputs including operating profit, loans, and net interest income. The results indicated that local banks demonstrated better efficiency based on the variable returns to scale (VRS) assumption, while banks owned by Nordic groups exhibited higher pure efficiency according to the constant returns to scale (CRS) assumption. The study contributes to the understanding of bank performance in a low-interest rate environment and provides valuable insights for the banking sector in Lithuania.

Similarly, with regard to banking efficiency, Endri et al.[13] introduce a study that aims to assess the efficiency of Islamic Rural Banks (BPRS) in Indonesia and identify the factors influencing their efficiency using a two-stage data envelopment analysis (DEA) approach. The DEA analysis focuses on production, intermediation, and the causes of inefficiency. The research utilizes financial reports from BPRS across Indonesia spanning the period of 2013–2021, obtained from the Financial Services Authority of Indonesia. The data is analyzed using a non-parametric two-stage DEA method, with input variables including personnel costs, fixed assets, and third-party funds. The findings reveal that revenue sharing, Return on Assets (ROA), and growth significantly and positively affect DEA efficiency. Bank Operational Costs (BOPO) and inflation have a positive but insignificant impact on DEA, while Non-Performing Loans (NPF) and Loan-to-Deposit

Ratio (FDR) have negative but insignificant effects. Additionally, the Capital Adequacy Ratio (CAR) exhibits a negative and nonsignificant effect on DEA.

Boubaker and Ngo[12] examine the performance and efficiency of 49 Islamic banks across 10 countries during the period of 2019–2020, with the aim of understanding how these banks can sustain their performance and resilience in the aftermath of the COVID-19 pandemic. Through the use of conventional inverse data envelopment analysis (InvDEA), the study finds that 31 out of the 49 banks would need to reduce their inputs in order to maintain their efficiency levels due to the reductions in their outputs caused by the pandemic. However, the proposed InvDEA efficiency model suggests that only 10 banks require such adjustments to preserve their efficiency. These adjustments would lead to cost savings, reduce inputs, and improve the overall efficiency of the examined banks, distinguishing them from the remaining 31 banks. The findings highlight the importance of adapting and optimizing input utilization for Islamic banks to enhance their performance post-pandemic.

In a more recently published study, Wu et al.[16] present a two-stage network data envelopment analysis (DEA) approach to assess the overall efficiency, fundraising efficiency, and fund use efficiency of Chinese commercial banks using data from 27 banks in the period from 2006 to 2020. In addition, Tobit regression was employed to further examine the influence of interest rate liberalization on bank efficiency. The results indicate that the liberalization of interest rates contributed to increasing the efficiency of banks, especially in the fundraising phase. However, this positive effect is not observed throughout the entire production process, as the liberalization of interest rates seems to impede the improvement of efficiency in the use of resources. This result raises concerns for Chinese commercial banks and deserves attention.

Table 1 summarizes the papers that deal with the topic.

Table 1. Synthesis of DEA works referring to banks.

Authors	Model used	Role guidance	Inputs	Outputs
Grmanová and Ivanová[2]	DEA-BCC-Oriented input	Production	Passive	Loans and advances to banks
			Operational costs	Non-Financial income
Cava et al.[5]	DEA-BCC-Oriented output	Production	Number of employees	Total deposits
			Operational expenses	Income not related to financial intermediation
			Fixed assets	-
Staub et al.[1]	DEA with panel data-VRS	Cost	Personnel expenses	Deposits
		Technique	Operational expenses	Provision net loans
		Allocative	Funding costs	Investments
Novickytė and Droždz[19]	DEA CCR and BCC	Production	Deposits	Operating profit
		Profitability	Labor expenses	Loans
		Intermediation	Debts to banks	Net interest revenue
Boubaker and Ngo[12]	InvDEA	Production	Operating expenses	Operating incomes
			Total deposits	Other earning assets
Endri et al.[13]	Two-stage network DEA	Production	Personnel costs	Revenue sharing
		Intermediation	Fixed assets	Return on Assets (ROA)
			Third-party funds	
Wu et al.[16]	Two-stage network DEA	Captation	Fund-raising	Operating profit
		Allocative	Interest rate	Non-Financial income

Source: elaborated by authors.

Thus, this work seeks to contribute to this literature by presenting empirical evidence for the comparative efficiency of 213 Brazilian banks and testing the hypotheses that larger banks are more efficient due to their scale[5].

3. Methodology

3.1. Data

The data used are available at the Central Bank of Brazil (BACEN) through Cosif, covering all financial institutions operating in the national territory. The data refer to the balance sheets reported by financial institutions on the base date of June 2019, in a total of 452 financial institutions.

Input variables:

1) Production-oriented model: administrative expenses, recruitment expenses, and personnel expenses;

2) Profitability-oriented model: total assets and total deposits.

Likewise, the variables used for outputs will be:

1) Production-oriented model: loan portfolio and deposits;

2) Profitability-oriented model: net income and earnings before taxes.

These variables were chosen in both models, similarly to what was found in the cited literature[1,19], as representations of the banks' production function and profit function. Of the 452 initial financial institutions, only banks that have deposit values and credit portfolios were selected. This left 213 banks.

Table 2 presents the tabulation of the dataset of all 213 banks and the descriptive analysis of the data used in the profit function-oriented model.

Table 2. Descriptive analysis of profit-oriented function data.

-	Total assets	Deposits	Net profit	Income before taxation
Average	41,453,035.29	14,392,982.38	355,233.16	494,891.18
Median	1,028,751.00	190,140.00	9,517.00	13,471.00
Standard deviation	201,170,753.94	74,380,196.75	1,774,233.02	2,549,388.49
Coefficient of variation	4.85	5.17	4.99	5.15
1st quartile	127,350.50	23,819.50	1,568.50	1,975.50
3rd quartile	6,844,245.00	1,706,975.00	58,139.50	88,714.00
Kurtosis	38.03	36.77	40.59	54.07

Source: elaborated by authors.

Likewise, **Table 3** presents the quantitative description of the model data-oriented to the production function.

Table 3. Descriptive analysis of the production-oriented function data.

-	Administrative costs	Funding expenses	Personal expenses	Credit portfolio	Deposits
Average	268,437.71	681,461.17	259,674.54	16,396,524.88	11,924,027.83
Median	12,476.00	10,864.00	8,941.00	394,533.00	189,958.00
Standard deviation	1,297,009.14	3,622,774.80	1,352,953.22	83,653,059.91	65,566,738.96
Coefficient of variation	4.83	5.32	5.21	5.10	5.50
1st quartile	2,366.00	968.00	1,960.00	48,580.50	22,245.00
3rd quartile	72,493.00	69,203.50	46,085.75	2,722,195.25	1,633,544.25
Kurtosis	50.85	48.54	46.14	42.20	46.12

Source: elaborated by authors.

3.2. Data envelopment analysis

Using the assumptions of the CCR model and the BCC model, we can distinguish two different types of efficiency—technical and scale efficiency. The input-oriented model is the most used to measure banking efficiency. This choice is likely to be based on the fact that bank managers have greater control over inputs (labor, among others) rather than outputs such as loans, income, etc. Duygun-Fethi and Pasiouras[21] and they manage the bank's cost centers when making strategic decisions.

In order to address the research problem, the proposed experimental design consisted of gathering financial information from the balance sheets of each bank available through the website of the Central Bank of Brazil IF. Data. Next, the selection of variables to be used in the models was carried out for both the production and profitability perspectives. Subsequently, the detection and exclusion of financial institutions considered outliers were performed using the jackstrap method. Afterward, the mentioned efficiency models DEA were applied, and the most efficient banks were obtained for each perspective, and finally, the results were analyzed.

A data envelopment analysis model (DEA) was used to evaluate relative efficiency with the assumption of constant returns to scale and variable returns to scale. Border analysis will be performed using two models, one oriented to production and the other oriented to profitability/profit as described by Novickytė and Drożdz[19] and Staub et al.[1]. Both models will be analyzed comparatively, with constant returns to scale and variable returns to scale. It was used this approach as a way of comparing the results found regarding the scale of banks and for evaluating public banks about production efficiency and possible profit-oriented inefficiency as described by Staub et al.[1].

The DEA technique compares the DMUs and presents a score for each one of them. DMUs with a score of 1 are efficient, while those with a score of less than 1 are inefficient. This score is determined by analyzing inputs and outputs. The inputs and outputs are determined by the manager or researcher, but what influences their choice is the purpose of the analysis[22].

To detect outliers, the Jackstrap technique is used, as it combines a jackknife scheme with bootstrap stochastic resampling, which reduces the computational cost. These expedients are used to calculate the influence of each observation on the production frontier. The jackstrap technique was used in the database with all DMUs with output orientation and variable returns to scale (VRS). In this way, after applying the jackstrap, the following rule was used to determine whether the DMU is an outlier:

$$\psi_J^{JK} > \psi^{JK}(n) \;=>\; Outlier$$

where the average of ψ are the average of the leverages (weights) determined by jackstrap.

About the production-oriented function, after applying the jackstrap method, 18 outliers were detected, which were removed from the DEA final application base, leaving 195 banks to be analyzed via the DEA model. Likewise, for the profit-oriented function, 19 outliers were detected, which were also removed from the application base, and 194 financial institutions were used for analysis.

For the estimation of efficiency, two analyses with different borders were used: with an orientation towards the production function and with an orientation towards the profitability/profit function after excluding outliers (18 banks). In all cases, the productivity drive was for output. An analysis with variable returns to scale and constant returns to scale was also performed to compare the results.

Output: oriented DEA model aims to maximize results, given the number of inputs according to the mathematical formulation explained below:

$$G_0 = Max_{\emptyset,\lambda}\, \emptyset$$

subject to

$$\emptyset_0 y_{0m} \leq \sum_{s=1}^{S} \lambda_S y_m, \qquad m = 1, \dots, M$$
$$x_{0k} \geq \sum_{s=1}^{S} x_{Sk} \lambda_S, \qquad k = 1, \dots, K$$
$$G_0 \geq 0, \qquad s = 1, \dots, S$$

4. Results

Applying the DEA-based efficiency measurement method as presented in the methodology section, we obtain the following results.

About the analysis of production-oriented efficiency with variable returns to scale, of the 195 banks, 28 were considered efficient, as shown in **Table 4**. The distribution of this orientation, separated by efficiency levels, is shown in **Figure 1**.

Table 4. Banks considered efficient, VRS, production orientation.

Institution	Benchmarks	Score
BB	5	100.00%
Caixa econômica federal	4	100.00%
Santander	7	100.00%
BNDES	51	100.00%
Banrisul	3	100.00%
Bancoob	48	100.00%
Bofa merrill lynch	22	100.00%
Volkswagen	19	100.00%
Nu pagamentos	100	100.00%
Pagseguro	0	100.00%
Mercedesbenz	5	100.00%
John deere bank	65	100.00%
Banco fidis	5	100.00%
Banco cargill SA	15	100.00%
Banco caterpillar SA	58	100.00%
Mercadopago.com	25	100.00%
Credicoamo rural credit cooperative	90	100.00%
Af develops Sp SA	4	100.00%
Bco Des. Do Es AS	3	100.00%
Banco ford SA	4	100.00%
Banco moneo SA	4	100.00%
Vr	3	100.00%
Komatsu bank of brazil	35	100.00%
Lecca	0	100.00%
Cooperative of doctors and other health professionals of joacaba	5	100.00%
Cooperative of municipal servants do sul fluminense ltda.	2	100.00%
Sanepar credisanepar employees' cooperative	54	100.00%
Escrediamento cooperative	39	100.00%

Source: elaborated by authors.

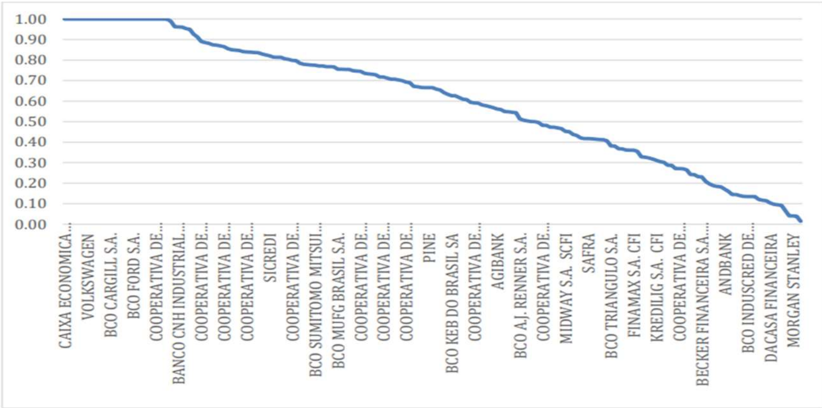

Figure 1. The distribution separated by efficiency levels, VRS, production orientation.

Source: elaborated by authors.

Likewise, in the analysis of production-oriented efficiency with constant returns to scale, only 16 were considered efficient, as shown in **Table 5**. The distribution of production orientation, CRS, separated by efficiency levels is shown in **Figure 2**.

Table 5. Banks considered efficient, CRS, production orientation.

Institution	Benchmark	Score
BNDES	22	100.00%
Bankoob	29	100.00%
Volkswagen bank	12	100.00%
Nu pagamentos	71	100.00%
John deere bank	82	100.00%
Banco fidis	15	100.00%
Banco cargill SA	21	100.00%
Banco caterpillar SA	79	100.00%
Mercadopago.com	34	100.00%
Creditoamo rural cooperative	99	100.00%
Af develops SP SA	Two	100.00%
Bco Des. do Es AS	8	100.00%
Banco ford SA	9	100.00%
Banco moneo SA	6	100.00%
Vr	10	100.00%
Komatsu bank of Brazil	50	100.00%

Source: elaborated by authors.

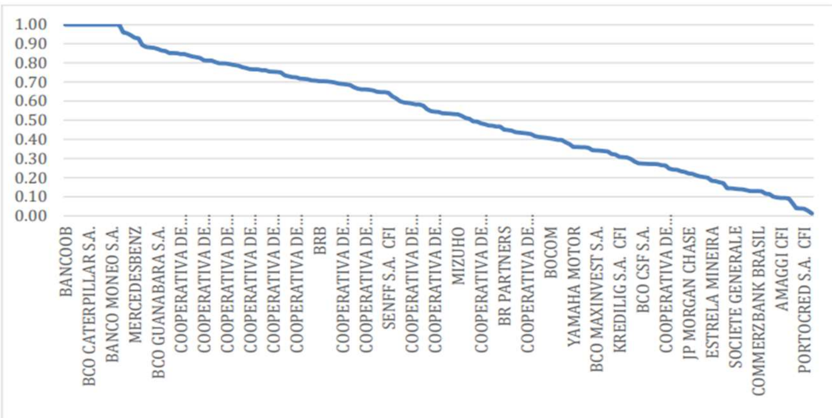

Figure 2. The distribution separated by efficiency levels, CRS, production orientation.

Source: elaborated by authors.

In the production-oriented model, the presence of new digital banks, such as Nu Pagamentos, Pagseguro, and Mercadopago.Com, can be seen within the efficiency frontier. About the analysis of efficiency oriented towards profitability/profit with variable returns to scale, of the 194 banks, 13 were considered efficient, as shown in **Table 6**, and the distribution of the number of banks separated by efficiency levels is shown in **Figure 3**.

Table 6. Banks considered efficient, VRS, profit orientation.

Institution	Benchmarks	Score
Itaú	1	100.00%
BNDES	29	100.00%
Bank daycoval SA	1	100.00%
Pagseguro	76	100.00%
Crefisa SA Cfi	57	100.00%
Banco fidis	3	100.00%
Banco cargill SA	9	100.00%
Bco AJ renner SA	Two	100.00%
Random bank	129	100.00%
Estrela mineira	16	100.00%
Cresal cooperative	13	100.00%
Oliveira dos brejinhos rural credit cooperative	11	100.00%
Credisanepar cooperative	60	100.00%

Source: elaborated by authors.

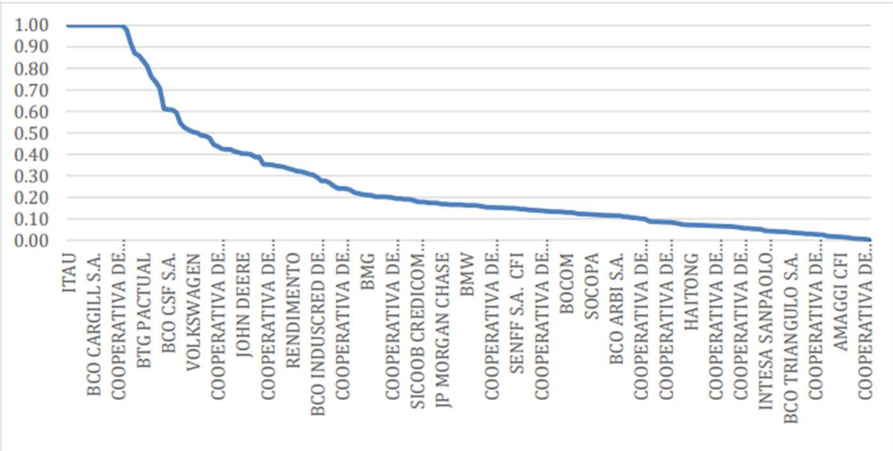

Figure 3. The distribution separated by efficiency levels, VRS, profit orientation.
Source: elaborated by authors.

Likewise, about the production-oriented efficiency analysis with constant returns to scale, only 3 were considered efficient, as shown in **Table 7**, and the distribution of this orientation, separated by efficiency levels, is shown in **Figure 4**.

Table 7. Banks considered efficient, CRS, profit orientation.

Institution	Benchmark	Score
Bco AJ Renner SA.	32	100.00%
Random bank	97	100.00%
Estrela mineira	36	100.00%

Source: elaborated by authors.

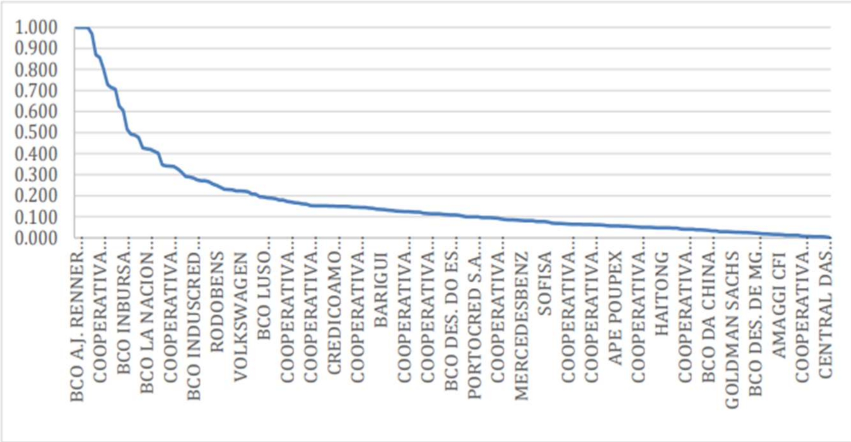

Figure 4. The distribution separated by efficiency levels, CRS, profit orientation.
Source: elaborated by authors.

About benchmarks, those that presented the most, in the production-oriented view, both for CRS and VRS, were the smaller banks, such as Nu Pagamentos, Credicoamo, and Banco Caterpillar. This is because the vast majority of the analyzed sample is from small banks; in this way, the smallest banks seek reference in another bank of similar size. In this context, the BNDES stood out as a benchmark for another 51 banks, being a reference not only for large banks but also for small banks.

As for profit/profitability-oriented analysis, small banks stand out, mainly Banco Randon, Banco Estrela Mineira, and Cooperativa Credisanepar. The possible explanation is the same as described for benchmarks with a production-oriented production function.

Differently from what happened with the production-oriented function, in the profit-oriented case, the new digital financial institutions, known as fintechs, did not present themselves on the efficiency frontier, justified by the fact that the vast majority of them still present poor financial results.

The average efficiency of the 195 banks analyzed, as well as the average efficiency of the 20% less efficient banks, are summarized in **Table 8**.

Table 8. Comparison of efficiencies by type of guidance.

Production and guidance role	Average efficiency	Average of the 20% least efficient
Production-CRS	0.54	0.17
Production-VRS	0.61	0.20
Profitability-CRS	0.18	0.03
Profitability-VRS	0.27	0.04

Source: elaborated by authors.

In addition, an attempt was made to analyze how each variable was correlated with efficiency. For that, the correlation coefficients of each input and output were calculated with the efficiency of scale oriented both to constant returns to scale and to variable returns to scale. The data are reported in **Table 9**.

Table 9. Correlation coefficients of variables by VRS and CRV methods.

Input and output variables	VRS correlation	CRS correlation
Administrative costs	0.1688	−0.1677
Funding expenses	0.1773	−0.1694
Guys	0.1825	−0.1615
Credit portfolio	0.2044	−0.1569
Deposits	0.2001	−0.1456
Active	0.3053	−0.1023
Deposits	0.2923	−0.1033
Net profit	0.3579	−0.0753
Income before taxation	−0.0352	−0.0207

Source: elaborated by authors.

5. Conclusion

The present work sought to analyze the efficiency of a wide range of banks operating in Brazil in the period before the COVID-19 pandemic and test the hypotheses that banks that are larger in scale and size are more efficient[5], in the same way that public banks are on the frontier of efficiency when oriented towards production[1]. For this, data from 213 databases and data envelopment analysis techniques are considered.

Thus, according to the proposed objective, we found that public banks are on the frontier of efficiency, with emphasis on BNDES and Banco do Brasil, when the analysis is directed towards production, in line with the results of Staub et al.[1]. About the hypothesis that the largest banks are on the frontier of efficiency, presented by Cava et al.[5], the results are ambiguous, so that in addition to most large banks being efficient, with an orientation towards production or profit, several other much smaller banks operating in niches are also considered efficient.

Among the efficient ones, it is worth highlighting the presence of new banks in the market, such as the fintechs Nu Pagamentos and Mercado Pago, when a function is focused on production. In the case of the measure of efficiency oriented towards profit/profitability, these banks show deficit results, which, therefore, do not appear on the frontier of efficiency in this regard. These findings are useful for the scientific literature on finance and banking by providing empirical evidence for the Brazilian banking sector with regard to sustainability and risk management for policymakers who work with banking regulation, as well as for other economic agents who seek to make more efficient decisions when investing in the sector.

As a suggestion for future research, it would be interesting to reassess these data shortly, after monetary and fiscal policies returned to neutrality without externalities from the COVID-19 pandemic, to compare the performance of large banks and fintechs after their growth with the search for profitability and gains in scale. The multicollinearity of data inputs and outputs was not overlooked, as in some models by Staub et al.[1]. In this sense, for greater completeness in future work on the subject, a two-step DEA analysis can be performed, as well as the use of newer DEA methods such as SBM or EBM in order to improve the results found.

Author contributions

Conceptualization, ACP and MST; methodology, ACP and MST; software, ACP and MST; validation, ACP and MST; formal analysis, ACP and MST; investigation, ACP and MST; resources, ACP and MST; data curation, ACP and MST; writing—original draft preparation, ACP and MST; writing—review and editing, ACP and MST; visualization, ACP and MST; supervision, ACP and MST; project administration, ACP and MST; funding acquisition, ACP and MST. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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