Determinants of bank efficiency: the Portuguese case

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ABSTRACT

Research background: Financial institutions; Banks; Other Depository Institutions

Purpose of the article: The objective of this study is to evaluate the technical efficiency of the Portuguese banking sector in the most recent period and to identify the determinants that explain it.

Methods: The methodology used consisted on the application of the non-parametric approach, Data Envelopment Analysis (DEA), to estimate the technical efficiency of the banks, in the period between the first semester of 2005 and the first semester of 2017. The analysis used the classic models CCR and BCC following the banking intermediation approach.

Findings & Value added: The results, in general, indicate that the level of efficiency of the Portuguese banking sector is high, suggesting that the banks operating in it are efficient in optimizing their resources. It also concludes that the determinants that influence efficiency are the size, the capital structure, the antiquity and the macroeconomic situation of the country.

To the best of our knowledge, this is the first approach to bank efficiency that involves time series data after the Portuguese sovereign debt crisis and, therefore, were not considered in previous studies.

The adversities that arose in the Portuguese banking sector, due to the financial crises that affected the country, and the constant competitive pressure of the sector, have made the efficiency of Portuguese banking institutions an essential factor for their survival. The adversities that arose in the Portuguese banking sector, due to the financial crises that affected the country, and the constant competitive pressure, made the efficiency of institutions an essential factor for their survival.

1. Introduction

The international financial crisis has led to increased instability in the financial markets and has led to the deterioration of the interbank market in the euro zone, exacerbating the unequal access conditions of countries to international financial markets. The Portuguese banking sector was one of the most affected by the crisis that arose in 2007, having been conditioned on its external financing and subject to high interest rate increases. In 2011, Portugal entered into a sovereign debt crisis, requesting international financial assistance as a result of the progressive deterioration of access conditions to international financing markets. During the period of sovereign debt crisis - between 2011 and 2014 -, profitability in the banking sector registered significant decreases, mainly due to the deterioration of the financial margin and reduction of the level of credit, as well as the increase of impairments and provisions. In order to face adversity and considering the competitive pressure, financial institutions were obliged to adopt policies to contain operating expenses, through a rationalization of productive factors, where efficiency had a crucial role for Portuguese banks if they remained competitive.

The research questions addressed are: what levels and how has the technical efficiency of the Portuguese banking sector evolved over the years? What impact did the international financial crisis and the Portuguese debt crisis have on the technical efficiency levels of the banks? What are the determinants of bank efficiency? The remainder of this paper is structured as follows: Section 2 provides a review of relevant literature. Section 3 details the method that will be used to address the research questions posed by this article. Section 4 data collection process; Section 5 presents the results; while Section 6 provides a conclusion.

2. Literature Review

There is a vast literature on bank efficiency that discusses the different aspects such as the role of internal and external factors and their impacts. The studies were conducted in several countries and regions, addressing the issues at different time periods and using various methods and tools to estimate efficiency.

Institutions of the Portuguese banking sector have also been the subject of empirical studies regarding their efficiency. Mendes and Rebelo (1999) applied a stochastic frontier model (SFA) developed an analysis of efficiency to the banking sector between 1990 and 1995. The authors affirm that the increase of the competition did not lead to an improvement in the performance with respect to the costs, and found that some of the banks analyzed were relatively more efficient in 1990 than in 1995. They also conclude that there is no obvious relationship between the size of the bank and cost efficiency. Another study, conducted by Camanho and Dyson (1999), measures the performance of a set of agencies of a Portuguese bank, using the DEA method. The authors conclude that the efficiency of the branches has positive effects on the banks' results. Looking at the protectionist past of the Portuguese banking system, Pinho (2001) points out that the low levels of competition that lasted until the early 1990s may have reduced the incentives for competition via costs. The author also concludes that the privatization policy was an important factor in reducing the levels of inefficiency in the sector. Canhoto and Dermine (2003) attempt to determine the impact of deregulation on efficiency by analyzing 20 Portuguese banks between 1990 and 1995. Using a nonparametric boundary estimated by the DEA method, the results show that new banks (created after 1984 through privatizations and deregulation of markets), and foreign banks outperformed the older banks (including public banks), and in the period of the analysis the increase in overall efficiency was observed. In an analysis of the production technology of Portuguese banks in the period between 1992 and 2004, Boucinha et al. (2010) show that banks operated, on average, with a level of inefficiency of around 9%. In the same research, the authors also note an acceleration of technological progress. Finally, Rebelo and Mendes (2000) and Lima (2008), in their respective investigations, show that mergers between banks contribute to an improvement in their performance.

3 Methodology

Basically two approaches to assessing bank efficiency are available in the literature. The parametric boundary approach is considered more complex and requires functional forms and hypotheses to construct an optimal stochastic boundary in order to measure efficiency. The most well-known nonparametric technique and the most widely used to measure efficiency is Data Envelopment Analysis (DEA).

It is an easy technique to handle multiple outputs and allows the evaluation of costs, technical costs and scale efficiencies without the need for direct knowledge of factor input prices. This is the main reason for its use in this study. Banker and Natarajan (2008) show how these values can be calculated using only the total expenditure data. In addition, total technical efficiency (TTE) is divided into pure technical efficiency (ETP) and efficiency of scale (EE). Technical inefficiency refers to the fact that a bank fails to produce the maximum outputs given its chosen combination of inputs, and the inefficiency of scale refers to the fact that the size of a DMU - Decision Making Units - smaller than optimal. Technically, inefficient banks are characterized by the use of a relatively excessive amount of inputs when compared to homologous banks operating with the same amount of outputs.

In the DEA model the production frontier is identified that represents the set of banks that are producing a certain quantity of outputs with the smallest number of inputs and the maximum result of 1 is attributed to the banks that are in that border. Efficiency results for banks that are not at the border are calculated by the ratio of inputs used by an efficient bank that produces comparable outputs and inputs used by a bank that is not at the border. Therefore, the results of a non-efficient bank vary between 0 and 1. The models can be mathematically formulated according to two approaches: oriented towards inputs or outputs. The first approach seeks efficiency by proportionally reducing the quantities of inputs to produce a given quantity of outputs, while the output-oriented approach seeks to maximize output levels using a specific amount of inputs. The estimation of the efficiency results of this study is based on the input-oriented approach.

3.1 CCR and BCC models

The CCR model measures the efficiency of each DMU that is obtained as a maximum of the ratio between the weighted sum of the outputs and the weighted sum of the inputs assuming constant returns to scale (CRS). The weights for the ratio are determined by the restriction that the similar proportions for each DMU must be less than or equal to unity, thus reducing the multiple inputs and outputs for a single "virtual" input and a single "virtual" output without requiring weights pre-assigned. Therefore, the efficiency score is a function of the weights or the "virtual" combination of inputs and outputs. Assuming that there are n DMUs, each with n inputs and outputs, the relative efficiency score for a given DMU_0 is obtained by solving the following linear programming model.

$$\max(\theta = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{r=1}^{m} v_i x_{i0}}) \quad \textbf{(1)}$$

Subject to $\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{r=1}^{m} v_i x_{i,j}} \leq 1; \; j = 1,2,...,n$

$v_i \geq 0$; i = 1,2, ..., m

$u_i \geq 0$; r = 1,2, ..., s

At where:

x_{ij} = amount of input i used by DMU j

y_{rj} = amount of output r produced by DMU j

v_i = weight given to input i

u_r = weight given to output r

After the transformation of Charnes and Cooper (1962), one can select a representative solution (v, u) for which:

$$\sum_{r=1}^{m} v_i x_{i0} = 1 \quad \textbf{(2)}$$

Thus, the denominator in the efficiency score θ is equal to one, the linear programming model transformed for DMU_0 can be (re) written as follows.

$$Max\theta = \sum_{r=1}^{s} u_r y_{r0} \qquad \textbf{(3)}$$

Subject to,

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{r=1}^{m} v_i x_{ij} \leq 0;\ j = 1,2,\dots,n$$

$$\sum_{r=1}^{m} v_i x_{i0} = 1$$

$v_i \geq 0$; $i = 1,2, \dots, m$

$u_i \geq 0$; $r = 1,2, \dots, s$

The linear programming model is executed n times in the identification of the efficiency score for all DMUs. Each DMU selects input and output weights that maximize its efficiency score. Generally, a DMU is considered efficient if it obtains a score of 1.00, implying 100% efficiency; considering a score lower than 1.00 implies that the DMU is relatively inefficient.

According to Coelli, et al. (2005), the CCR model, which assumes constant scale returns (CRS), is only appropriate when a bank operates on an optimal scale. In practice there are some factors that can cause the bank to not operate at an optimal level (for example, imperfect competition). To allow this possibility, we introduce the BCC model that assumes variable returns (VRS) and measures the pure technical efficiency for each of the sample banks. As a rule, the BCC model generates pure technical efficiency scores equal to or greater than the ETT results obtained with the CCR model.

The efficiency of scale (EE) can be measured by dividing the efficiency score of the CCR model by the efficiency score of the BCC model, given by:

$$EE = \frac{CRS_{ET}}{VRS_{ET}} = \frac{ETT}{ETP} \qquad \textbf{(4)}$$

From the BCC model, it is possible to analyze if the production of a bank presents increasing returns to scale, constant or decreasing by the signal of the variable. According to Färe, Grosskopf and Lovell (1985) and Coelli, et al. (2005), the BCC model is presented as follows:

$$Max\, E_k = \sum u_r y_{rk} + w_k ; r = 1,\ldots, s \qquad \textbf{(5)}$$

Subject to,

$$\sum v_i X_{i,k} = 1; i = 1,\ldots, m$$
$$\sum u_r Y_{r,j} - \sum v_i X_{i,j} + w_k \leq 0; j = 1,\ldots n$$
$$v_1,\ldots v_s > 0$$
$$u_1,\ldots u_m > 0$$

The present study determines the efficiency score through both models, BCC and CCR, to define the three types of technical efficiency (ETT, ETP, EE) for each bank.

3.2 Selection of variables

The selection of the variables for input and output is considered a critical step in the execution of the efficiency evaluation using the DEA approach. The discussion is about the optimal sample size (DMU number) compared to the number of inputs and outputs; and on which variables are most suitable for determining efficiency. Boussofiane, Dyson and Thanassoulis (1991) stipulate that in order to obtain good discriminatory power of the CCR and BCC models, the minimum limit of the number of DMUs to be studied must be the product between number of inputs and outputs. Siems and Barr (1998) mention some considerations to be taken into account in the appropriate selection of bank variables. According to these, the inputs and outputs should reflect their importance and contribution in attracting deposits and lending. In addition, the selection of variables depends on the type of approach used for the study: production or intermediation. In the intermediation approach (followed in this study), the bank acts as a financial intermediary, seeking to transform the deposits collected in credit and investments to its clients. Under this approach, the variables that best fit the objectives of the study and that most contribute to the answer to the research questions (table 1) were selected. In this way, two outputs (loans to customers and financial assets held for sale) and four inputs (deposits, other tangible assets, personnel expenses and expenses with impairments arising from loans granted to customers) were used.

Table 1: Input and output variables used in the DEA model

Intermediation Approach	
Inputs	Customer Resources (Deposits) Other Tangible Assets Imparities Staff expenses
Outputs	Customer Loans (Gross) Financial Assets Held for Sale Customer Loans (Gross) Financial Assets Held for Sale

4. Date

4.1 Overview of the Portuguese Banking Sector

Until 2007, the Portuguese banking sector benefited from a favorable international financial environment characterized by progressive globalization and favorable financing conditions, both in terms of the cost and the amount of funds available. This context facilitated the expansion of the activity of the sector, which registered a continuous growth, evaluated by assets, with credit being the main component and also resulting in improvements in profitability and risk indicators.

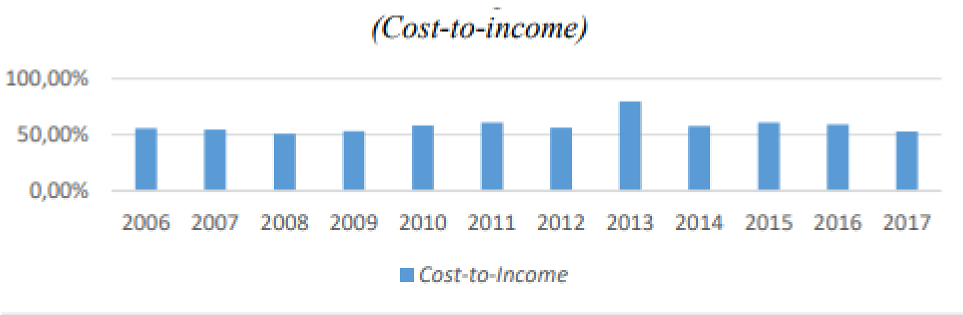
The global financial environment has substantially changed since the summer of 2007. The emergence of the international financial crisis, which affected Europe more directly from 2008 onwards, and subsequently the sovereign debt crisis in the euro area, reversed the trend of growth in the sector for many years and exposed its weaknesses. Since then, the sector has had to develop the activity in an adverse environment, aggravated by the economic recession of 2010-2014, which meant a reduction in the volume of financial services transacted, the deterioration of risk and a sharp decrease in the levels of profitability of institutions. In 2012, BCP, BPI and CGD were recapitalised and, in August 2014, the BOP applied a resolution measure to BES following a loss of around EUR 3.6 billion in the first half of 2014. In December of 2015, it was BANIF's turn. The BOP stated that the bank was failing or likely to fail and considered that the application of a settlement measure was the only solution capable of protecting depositors and ensuring continuity of the bank. In December 2017 Banco Popular Portugal was acquired by Banco Santander Totta, and ceased to exist as a legal entity.

A density acentuated the return between 2010 and 2016 is, in just in the determination of the income financial debtised the disclosure of laws and reduction the level of credit the risk of increase the amount of provision and provision.

In this context, and taking into account the limited capacity of banking product generation, as the changes occurred in the sector must have occurred, in part, without increasing efficiency, by reducing operating costs. Operational efficiency, measured by cost of provision, is an important indicator for assessing the efficiency of institutions. The sectoral turnaround of this indicator is somewhat erratic (see figure 1).

Graph 1: Evolution of the Efficiency Ratio

Operational efficiency



Fonte: APB

By 2008, efficiency ratios should be gradual in 2013 and 2015. These are the key indicators of market deterioration. Thus, it will become a probability of growth and growth of the cost industry, especially a personnel cost performance. 4.2 Selection of Sample and Data A table of banks selected for the study contemplates the values of 85% of the market share of the entire banking sector, a bank control table (table 2). An analysis was made for a time horizon of 12 and a half years, between January 2005 and June 2017, using a semiannual periodicity, comprising a set of 25 periods.

Table2: Sample weight in total assets of the Portuguese banking sector (Thousands of Euros)

2005	1º Sem.	288 738 701	248 792 229	86%
	2º Sem.	325 847 456	272 263 432	84%
2006	1º Sem.	351 651 000	303 488 295	86%
	2º Sem.	384 353 000	315 216 237	82%
2007	1º Sem.	422 391 000	343 034 853	81%
	2º Sem.	443 458 000	360 652 777	81%
2008	1º Sem.	463 730 000	381 707 192	82%
	2º Sem.	476 883 000	402 435 719	84%
2009	1º Sem.	490 437 000	427 594 496	87%
	2º Sem.	510 587 000	434 043 515	85%
2010	1º Sem.	530 222 000	454 812 807	86%
	2º Sem.	531 721 000	453 878 702	85%
2011	1º Sem.	522 293 000	457 311 227	88%
	2º Sem.	512 611 000	446 883 014	87%
2012	1º Sem.	511 766 000	435 484 731	85%
	2º Sem.	496 148 000	421 416 860	85%
2013	1º Sem.	477 564 000	409 830 208	86%
	2º Sem.	460 204 000	407 801 134	89%
2014	1º Sem.	449 357 000	381 577 974	85%
	2º Sem.	425 697 000	359 998 170	85%
2015	1º Sem.	420 062 000	351 652 140	84%
	2º Sem.	407 589 000	344 355 092	84%
2016	1º Sem.	399 186 000	341 388 073	86%
	2º Sem.	385 894 000	324 772 246	84%
2017	1º Sem.	384 000 000	324 803 604	85%
			Média	85%

Fonte: APB e BdP

Year	Total active sample	Total active sample	Weight (%)

The collection of data consisted of the compilation of accounting data of data registered in databases and the information databases of APB - Associação Portuguesa de Bancos. Existing foreign exchange operations and credit operations and therefore perform universal banking operations. Present is an unbalanced panel of data.

4.3. Characterization of Sample Banks

Table 3 presents as main characteristics of each database and the information is useful for the development of the analysis.

Table 3: main features of the sample banks

Bank	Year of creation	Capital Property	Origin of Capital	Market Shares
CGD	1876	Público	Nacional	21,34%
Millennium BCP	1985	Privado	Estrangeiro	15,52%
Santander Totta	1988	Privado	Estrangeiro	9,43%
NB	1920	Privado	Estrangeiro	13,33%
BPI	1985	Privado	Estrangeiro	9,04%
MG	1840	Privado	Estrangeiro	6,13%
CCAM	1911	Privado	Nacional	3,51%
BANIF	1988	Privado	Nacional	3,32%
B. Popular	1991	Privado	Estrangeiro	2,14%
BIC	2008	Privado	Estrangeiro	1,44%

As shown, the antiquity of the sample banks is not homogeneous. The two oldest banking entities are MG and CGD. CGD represents the public bank present in the sample and the capital of all banks that are mostly of foreign origin. It also has a market share of each bank. With this indicator, you must register with CGD, BCP and NB are the three largest banks.

Table 4 presents the descriptive statistics of each of the variables used to determine the banks' capacity throughout the sample period.

Table 4: Descriptive statistics of the explanatory variables (Thousands Euros)

	Inputs				***Outputs***	
Description	Customer Resources (Deposits)	Impairment for Credit	Other Tangible Assets	Cost with staff	Customer Loans (Gross)	Financial Assets Held for Sale
Average	20.121.159	1.180.104	273.675,2	155.300,7	26.372.981	6.239.027
Medium	13.620.187	522.536	228.619	131.405	22.879.077	5.127.101
Maximum	73.426.265	5.637.351	1.228.192	531.017	85.294.548	24.748.551
Minimum	96.476	113	2.857	2.011	153.314	4.080
Standard deviation	18.225.391	1.463.057	269.691,7	131.687,1	21.422.443	5.385.873
Observations	229	229	229	229	229	229

The companies reveal that, in a general way, the standard deviations of the different variables are high, which shows a heterogeneity among the banks.

5. Empirical results

5.1 CCR model

In Table 5, the results of the total technique are presented for the entire sample period.

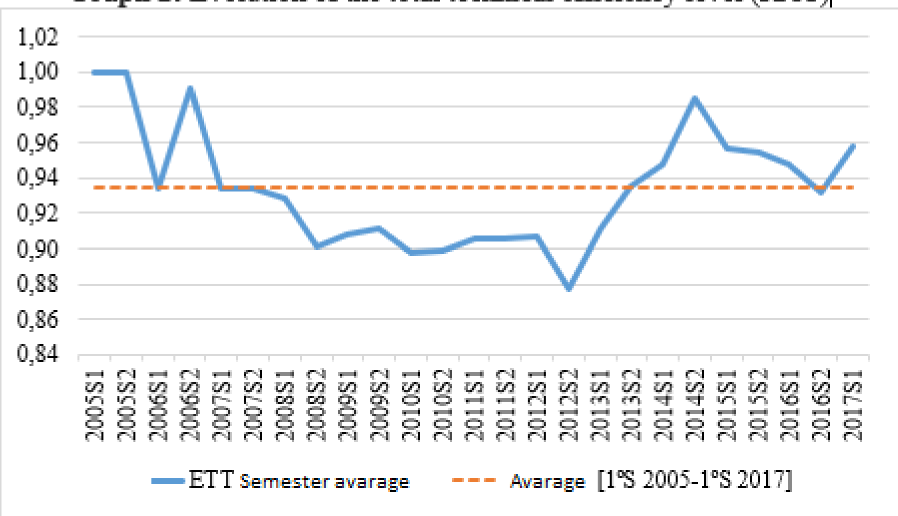
Table 5: Total Technical Efficiency Scores (RACs)

Semester	Number of Banks in the Sample	Average	Standard deviation	Minimum	Maximum	Number of Efficient Banks
2005S1	6	1,00000	0,00000	1,00000	1	6
2005S2	6	1,00000	0,00000	1,00000	1	6
2006S1	8	0,93380	0,13062	0,65077	1	6
2006S2	8	0,99092	0,02568	0,92737	1	7
2007S1	9	0,93354	0,19749	0,45191	1	7
2007S2	9	0,93417	0,18018	0,40754	1	8
2008S1	9	0,92798	0,20673	0,45288	1	6
2008S2	9	0,90103	0,18908	0,40417	1	6
2009S1	9	0,90844	0,18447	0,45983	1	6
2009S2	10	0,91149	0,17668	0,46886	1	7

2010S1	10	0,89750	0,19373	0,41853	1	6
2010S2	10	0,89865	0,20048	0,38152	1	5
2011S1	10	0,90541	0,20079	0,37676	1	6
2011S2	10	0,90580	0,14733	0,55099	1	5
2012S1	10	0,90657	0,14398	0,55767	1	5
2012S2	10	0,87680	0,15695	0,53958	1	3
2013S1	10	0,91183	0,13477	0,64032	1	4
2013S2	10	0,93528	0,12907	0,65742	1	5
2014S1	10	0,94797	0,09642	0,74654	1	6
2014S2	10	0,98534	0,02517	0,93068	1	7
2015S1	10	0,95724	0,06550	0,81974	1	5
2015S2	9	0,95495	0,07723	0,79537	1	5
2016S1	9	0,94730	0,07671	0,78724	1	5
2016S2	9	0,93187	0,11022	0,70075	1	6
2017S1	9	0,95768	0,08428	0,79520	1	7

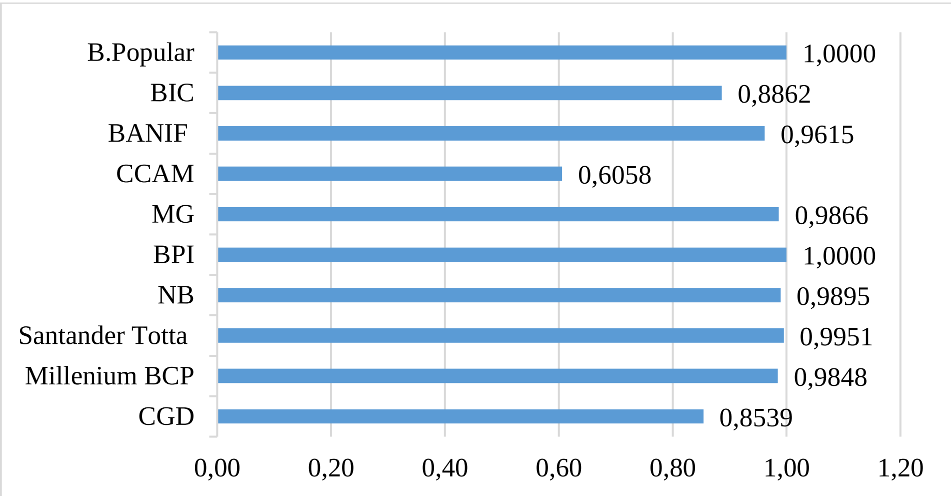
The number of banks is inconstant during the sample period due to the merger processes and the occurrence and emergence of new actions. The total technical efficiency of the average of the banks, also observing the number of banks in variable time over the years. The efficiency scores in table 5 show that the second half of 2012 and the first half of 2013 show the largest number of technically inefficient banks. The evolution of the efficiency level for the sampling period (graph 2) reveals some irregularity, however, the average of 93.4% - the need for efficiency levels of the banks operating in Portugal are high.

Graph 2: Evolution of the total technical efficiency level (RAC)



Between the end of 2007 and the second half of 2012 there is a significant decrease in TTE, and by verification verify that, in this period, its lowest value. In the second half of 2012 the banks operated with an average level of inefficiency of 14%. Aside from this, the following four lessons note the significant increase in the level of ETT, which reveals the bank's effort to optimize its resources. The mean ETT of each bank (graph 3) shows that the two sources were fully used throughout the time horizon of the sample. However, ETT scores that show the probability of inefficiency are less than 1.6%, which reveals this information also very efficiently. On the other hand, the CCAM was the least technically efficient bank in the sample, with an average level of inefficiency of 39.4%.

Graph 3: Average total technical efficiency per bank (Q1 2005-1S 2017)



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5.2 BCC model

Table 6 shows the ETP results for the entire sample period.

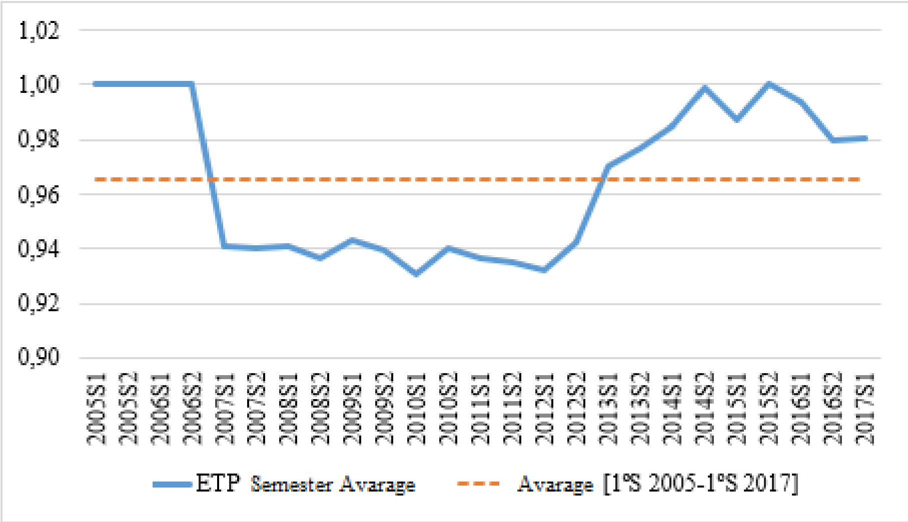
Table 6: Pure Technical Efficiency Scores (BCC)

Semester	Number of Banks in the Sample	Average	Standard deviation	Minimum	Maximum	Number of Efficient Banks
2005S1	6	1,00000	0,00000	1,00000	1	6
2005S2	6	1,00000	0,00000	1,00000	1	6
2006S1	8	1,00000	0,00000	1,00000	1	8

2006S2	8	1,00000	0,00000	1,00000	1	8
2007S1	9	0,94066	0,17946	0,46591	1	8
2007S2	9	0,94018	0,17391	0,46161	1	8
2008S1	9	0,94115	0,19043	0,47743	1	7
2008S2	9	0,93652	0,17000	0,42872	1	8
2009S1	9	0,94333	0,17565	0,48999	1	8
2009S2	10	0,93971	0,16696	0,46890	1	8
2010S1	10	0,93057	0,17800	0,43799	1	8
2010S2	10	0,93990	0,18969	0,40003	1	8
2011S1	10	0,93664	0,19195	0,39076	1	8
2011S2	10	0,93540	0,14098	0,55158	1	7
2012S1	10	0,93192	0,13878	0,56631	1	7
2012S2	10	0,94250	0,14556	0,54157	1	8
2013S1	10	0,96993	0,09510	0,69926	1	9
2013S2	10	0,97674	0,07208	0,77164	1	8
2014S1	10	0,98473	0,04234	0,86531	1	8
2014S2	10	0,99871	0,00409	0,98707	1	9
2015S1	10	0,98733	0,04007	0,87328	1	9
2015S2	9	1,00000	0,00000	1,00000	1	9
2016S1	9	0,99398	0,01805	0,94585	1	8
2016S2	9	0,97993	0,06022	0,81935	1	8
2017S1	9	0,98049	0,05852	0,82445	1	8

Observing the ETP values, it checks if a given difference is relative to the previous ETT results. Revealing a trend consistent with other studies, it was found that the ETP results were obtained in the ETT scores estimated from the CCR model. Efficiency scores show a high number of databases in each period. Comparing the number of data between the two models, it verifies if the ETP scores point to a greater number of databases, being a greater asymmetry Accomplished in the second half of 2012 and first of 2013.
Graph 4 shows the level of pure technical efficacy for the entire sample period.

Graph 4: Evolution of the pure technical efficiency level (BCC)



The average of 96.5% was higher than the ETT average by three percentage points. In the first half of 2007 the companies operated at an average level of inefficiency of 6.3%, and this trend remained limited during the following years. From the second half of 2012 until the end of 2014, there is a significant increase in the level of ETP, evidencing high average values. The mean ETP model evolved in a low hierarchical fashion, but averaged 2%.

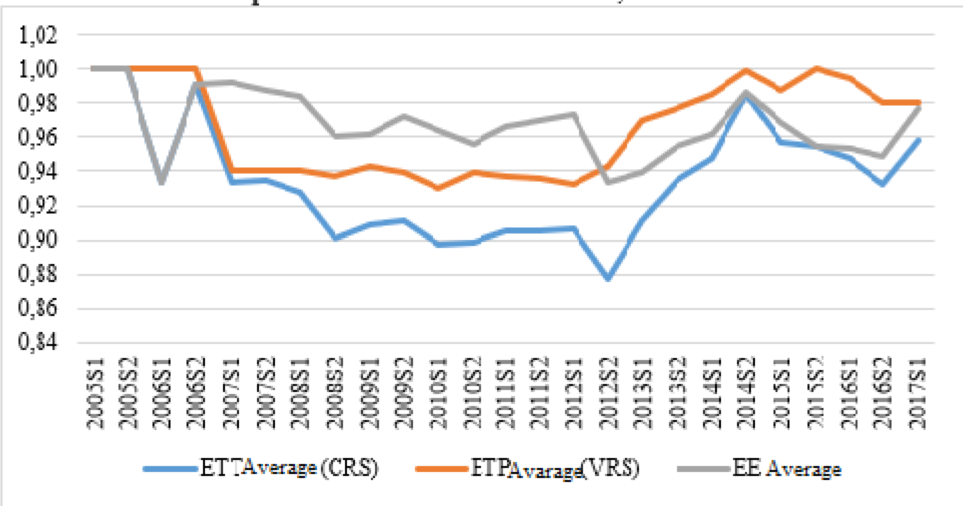
The results of the average ETP per bank, as recorded in the ETT, confirm that the CCAM is the least efficient bank in the sample, with an average level of pure technical inefficiency of 35.8%. The number of banks elected in the interest rate, assuming the CRS and VRS assumption, was significantly lower, however, as in the previous year.

5.3 Efficiency of Scale

From the ratio between the ETT score and the ETP score, the efficiency of the scale was estimated. The EE scores show an average of 96.7%, being higher than the means of ETT (93.4%) and ETP (96.5%). In addition, over the entire sample period, EE presents an average number of 6 fully efficient banks in each observed period.

The comparative results of the three efficiency types analyzed (Figure 5) show that between the first half of 2007 and the first half of 2012, scaling efficiency scores were always higher than pure technical efficiency scores. During this period, the total technical inefficiency of banks is more attributable to pure technical inefficiency than to inefficiency of scale. This suggests that some of the banks did not use the most efficient available technology.

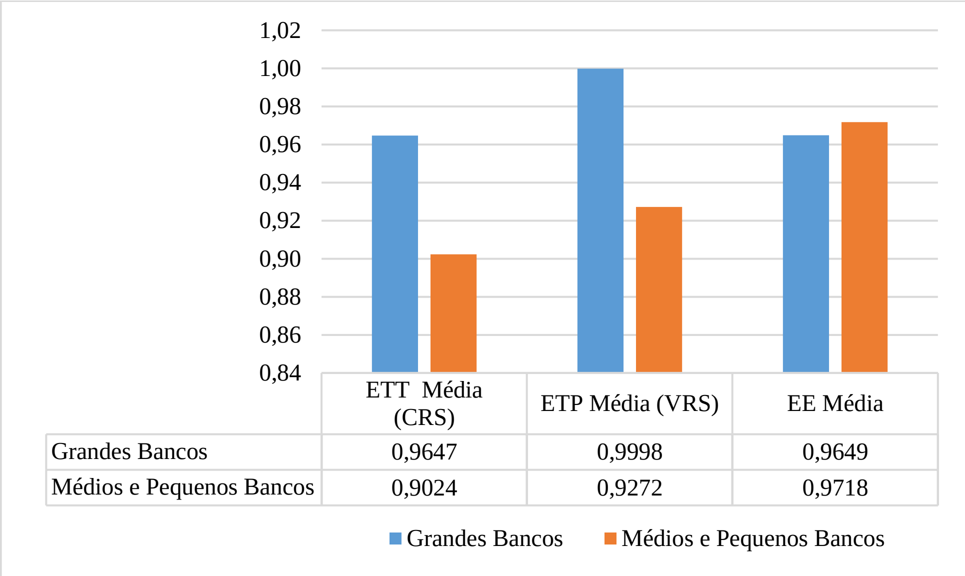
Graph 5: Evolution of the level of ETT, ETP and EE



5.4 Technical Efficiency and Dimension

The procedure of this analysis consisted in the classification of the banks by size being considered the weight of the asset of each bank relative to the total of the assets of the banking sector. Taking advantage of the values presented in table 3, the banks were divided into two groups using as criterion a superior asset (large) or lower (medium and small) to 8.5% of the total of the sector. Graph 6 summarizes the average ETT, ETP and EE for the sample period considering the size of the banks.

Graph 6: Relation between technical efficiency and the size of banks

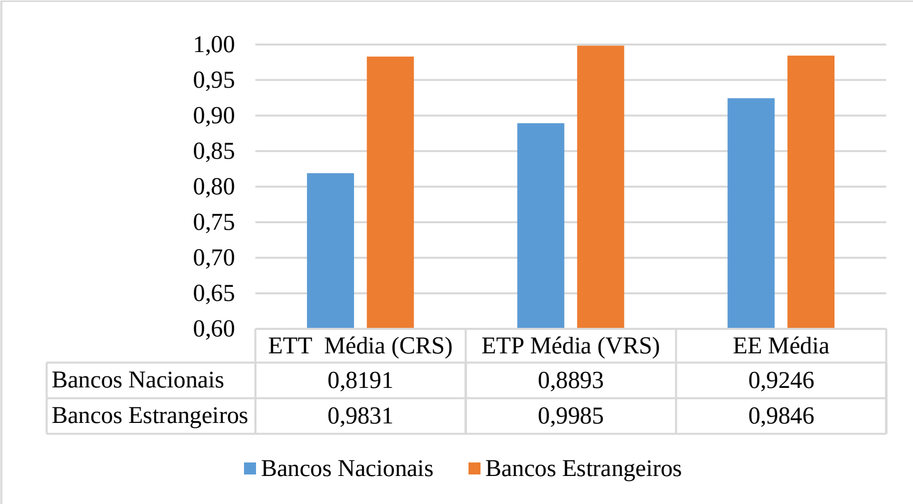


Larger banks have the highest ETT and ETP results, but smaller institutions are more efficient in scale. According to the literature, the total technical efficiency value can be partly explained by the existence of scale inefficiencies, meaning that the true efficiency of a bank may be even higher. This fact is observed in the graph, which reveals an increase of ETP in relation to the ETT for both groups of banks. Scale efficiency values show that medium and small banks are more efficient, which produces an incentive to be more efficient in terms of ETP, however this is not observed since larger institutions show only 1 % less efficient than the rest.

5.5 Technical efficiency and origin of capital

Two groups of institutions that are characterized by the origin of their capital were considered in the analysis: national and foreign capital banks. The results are illustrated in Figure 7, which shows the estimated mean efficiency scores for the two groups.

Graph 7: Relation between technical efficiency and the origin of capital



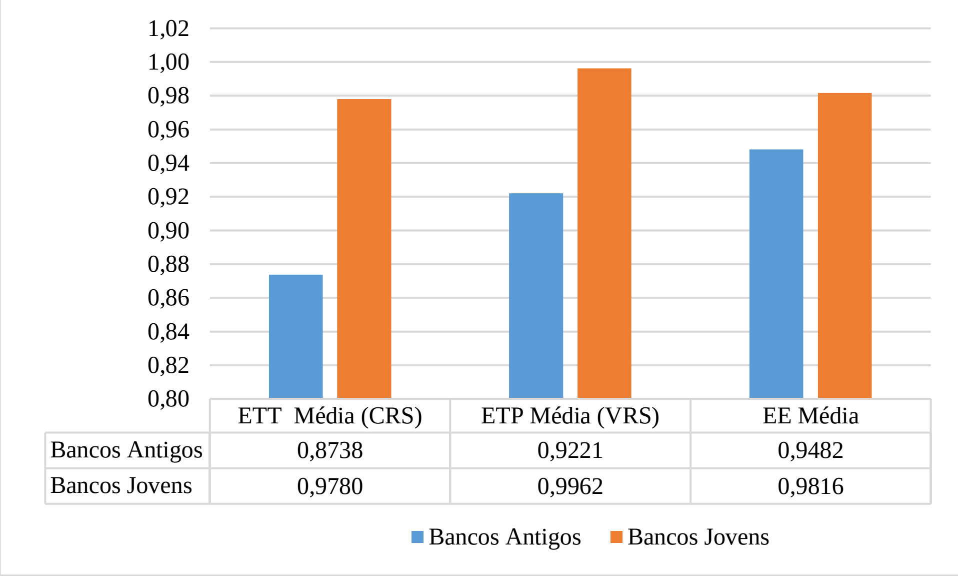
	ETT Média (CRS)	ETP Média (VRS)	EE Média
Bancos Nacionais	0,8191	0,8893	0,9246
Bancos Estrangeiros	0,9831	0,9985	0,9846

Foreign banks proved to be more efficient during the 25 semesters of the sample period. Domestic banks operated, on average, at a technical inefficiency level of 18%, while foreign banks showed only 2% inefficiency. Observing the results of ETP, it can be seen that foreign banks were almost optimal in the use of their inputs, while domestic banks used, on average, 11% more resources to produce the outputs. In addition to the results of ETT and ETP, the results of scale efficiency also show the foreign entities as more efficient. It is plausible to conclude that foreign investment has a positive influence on the efficiency of the Portuguese banking sector, possibly because shareholders introduce differentiated management practices that appear to be advantageous in the efficiency of banks operating in Portugal.

5.6 Technical efficiency and seniority of banks

Following the study by Canhoto and Dermine (2003), which investigated bank efficiency in Portugal between 1990 and 1995, comparing old and new banks, an analysis was made of the relationship between technical efficiency and seniority of banks. The group of young banks includes entities constituted from 1985 onwards. The results show that the most recent banks were technically more efficient (Chart 8).

Graph 8: Relation between technical efficiency and seniority of banks

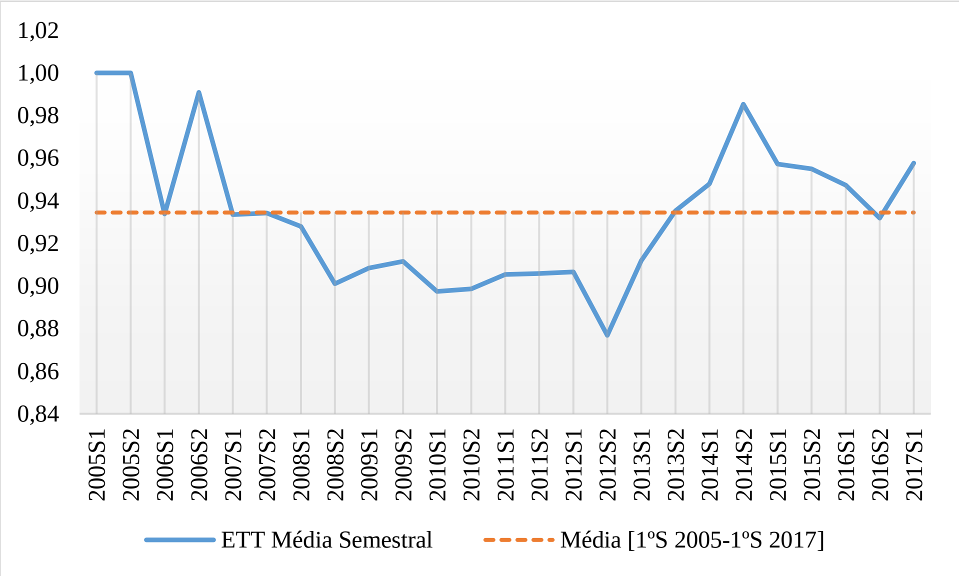


The older banks were, on average, ten percent more inefficient in terms of ETT. In addition, evidence of ETP and EE reinforce the conclusion, and in terms of ETP the most recent banks have proven to be nearly 100 per cent efficient while the older banks operated, on average, with a ETP level of 92 per cent. These conclusions are compatible with the results obtained by Canhoto and Dermine (2003).

5.7 Technical Efficiency and Financial Crisis

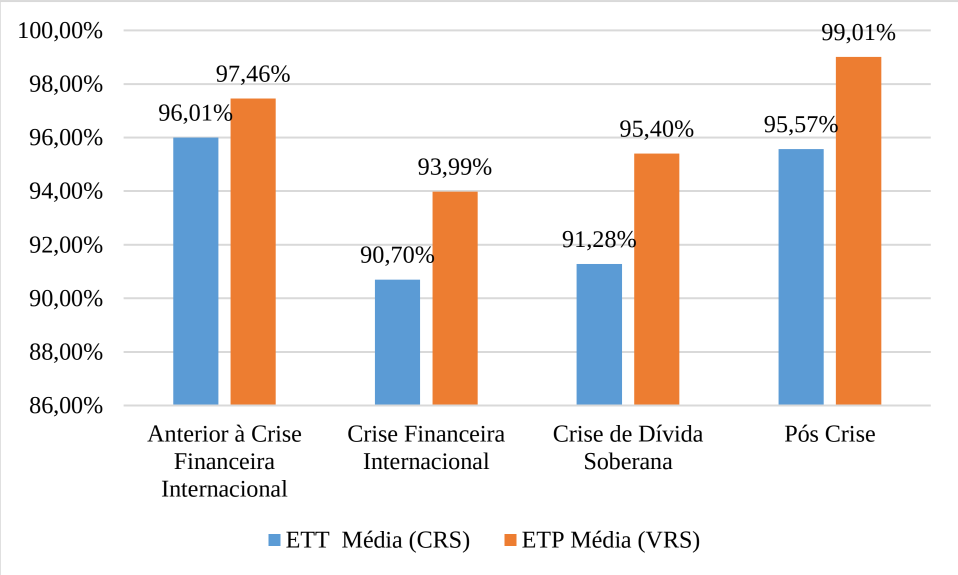
In order to test the effects of the international financial crises and the Portuguese debt on the technical efficiency of the banks, the sample period was divided into four subperiods: prior to the international financial crisis (Q1 2005-1S 2008); period of international financial crisis (2nd S 2008-2nd 2009); period of the sovereign debt crisis (1S 2011-1S 2014); and post-crisis (2nd S 2014-1 2017). Graph 9 shows the evolution of the banks' total technical efficiency during the intervals mentioned.

Graph 9: Evolution of the average ETT level during periods of crisis



In the period before the international financial crisis, the technical efficiency of the banks presents some irregularity but the observed values are high. As of the first half of 2008, the level of the ETT shows a downward trend that runs through the crisis period, with the values registered below the sample average. In the period of the sovereign debt crisis, the level of the ETT follows the same trend, observing in the second half of 2012 the lowest value of the sample. From the following semester, ETT values increase abruptly, with the sovereign debt crisis ending with values above the total average. Finally, in the post-crisis period, the banks presented high technical efficiency values. To consolidate these conclusions, the averages of ETT and ETP are presented in graph 10 for each of the time intervals considered.

Graph 10: Mean ETT and ETP in the four time periods considered

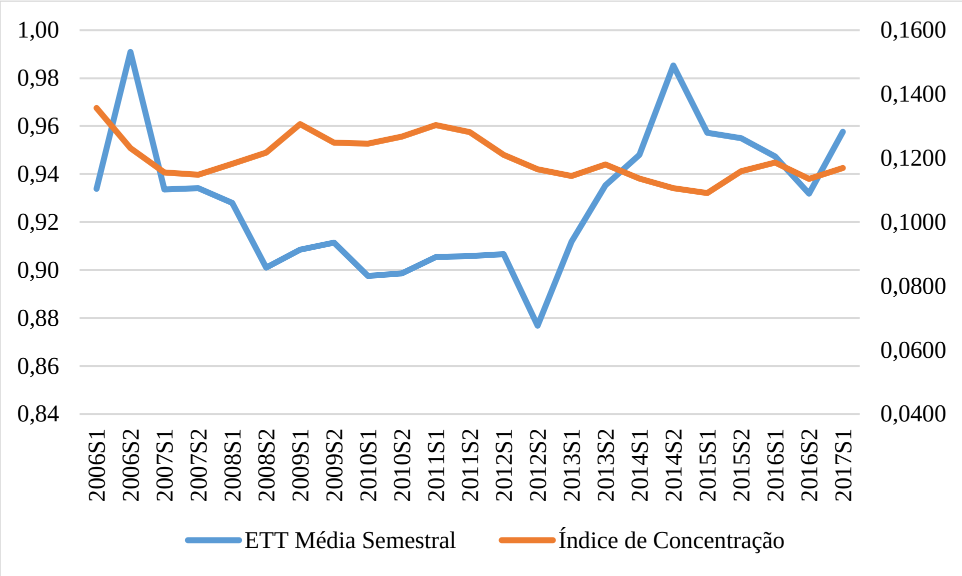


It appears that the international financial crisis has affected bank efficiency, leading to an increase in total technical inefficiency and pure technical inefficiency. In the period of sovereign debt crisis, banks presented averages of ETT and ETP of 91.2% and 95.4% respectively. The graph also reveals that in the last period, post crisis, the means of ETT and ETP experienced a significant increase, observing a 4.3 percent improvement in ETT and 3.6 percent in ETP. This evidence makes it clear that banks were less efficient in times of crisis, causing a negative impact on the technical efficiency of banks in Portugal.

5.8 Technical Efficiency and Industry Concentration

To analyze the influence of the level of competition on the efficiency of banks, the banking concentration was calculated using the Hirschman-Herfindahl index for the sample period. The values obtained, ranging from 0.109 to 0.135, have a mean of 0.120, indicating a moderate-low concentration level. Graph 11 compares the half-year evolution of the ETT with the values obtained for the sectoral concentration index.

Graph 11: Relationship between the evolution of the mean ETT and the concentration index



There is no discernible relationship between efficiency and concentration of the industry. This difficulty in identifying a link between the two indicators can be explained mainly by the fact that the concentration index does not show large oscillations over the time interval. To support the analysis, the correlation coefficient between the concentration index and the ETT, ETP and EE were used, but the results (table 7) show that there is no significant association between the efficiency scores and the concentration index.

Table 6: Correlation coefficient between concentration index and efficiency

	ETT Average	**ETP Average**	**EE Average**
Concentration Index	-0,42533	-0,33066	0,36472

6. Conclusions

This study analyzes the technical efficiency of the Portuguese banking sector in the recent period (2005-2017) using Data Envelopment Analysis. It is another contribution to the recent literature on bank efficiency in Portugal considering a country and a particular institutional structure. It uses two classic models of non-parametric approach, named in the literature by CCR and BCC, that allow to estimate the values of total technical

efficiency, pure technical efficiency and scale efficiency for a sample of the ten largest banks operating in Portugal.
The results obtained show that the efficiency levels of the banking sector between 2005 and 2017 were high, suggesting that banks are efficient in optimizing their resources. While satisfactory, the figures also show that there is still room to improve the technical efficiency of banking. Its evolution presented some irregularity over time, however it can be affirmed that it evidenced an increasing tendency indicating that the Portuguese banking has been developing a set of efforts aimed at increasing its efficiency.

With regard to the identification of efficiency determinants, the results provide evidence that size is an important factor for technical banking efficiency. Larger institutions are more efficient. The evidence also favors the hypothesis of advantage in terms of the origin of capital. Foreign banks were more technically efficient than their domestic counterparts. It is worth mentioning that most banks with foreign participation resulted from the acquisition of national banks (public and private), which suggests that greater technical efficiency can be assessed in the context of the M & A activity. It is thus plausible to conclude that foreign investment in Portuguese banking has a positive influence on the efficiency of the sector.
The age of institutions is another factor explaining the level of technical efficiency. Younger banks are more efficient. According to the estimated technical efficiency scores, these were, on average, 10 percent more efficient, inferring the negative influence of the banks' antiquity on their efficiency.
Banks' efficiency varies over time and appears to respond to macroeconomic and financial shocks. The results of this study demonstrate that banks were less efficient during the periods of crisis that affected Portugal. Finally, it is interesting to note that no significant impact was observed due to the concentration of the market and that the existence of a relationship between the efficiency of the banks and the competition inherent in the sector was maintained.

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