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Portuguese banks' performance: comparing efficiency with their Spanish counterparts

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Abstract Using the intermediation approach, where banks are seen as intermediaries between savers and investors, receiving deposits and providing loans, we study the efficiency of Portuguese Banks, using data from 2008 until 2013 from BankScope Database. In the first stage, data envelopment analysis is applied in order to measure efficiency. We extend this analysis to the major Spanish banks and compare the results. Given the 6-year period, the results highlight better efficiency scores for the 14 Spanish banks with an average of 0.815, comparing with the 10 Portuguese banks, which exhibit an average score of 0.783. We cover the recent financial crisis period, to ascertain if there are significant differences between the two neighbouring countries. In the second stage, we use the generalized linear models approach, applying a fractional response model, in order to explain the efficiency scores. In this stage, we use as potential explanatory variables bank specific attributes and country-specific and institutional variables. Our results indicate that the characteristics of each bank appear important to explain efficiency, particularly liquidity, and the level of financial development of a country. Additionally we investigate if there are structural differences between the two countries.

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The results of the Chow test indicate that we do not reject the hypothesis that the determinants of bank efficiency are the same in both countries.

Keywords Banking · Data envelopment analysis · Efficiency · Fractional response models

JEL Classification G21 · C67 · C35

1 Introduction

The analysis of efficiency in the financial sector has given rise to a large number of studies. In fact, many authors have measured efficiency in the banking sector in different countries and circumstances. Measuring bank efficiency is a very important issue, both from the academic point of view and from an operational perspective. In the banking sector, high levels of competition from traditional business and the emergence of alternative distribution channels of banking products and services makes the control of the entities' performance an element of increasing interest. Information on efficiency levels can be used to improve management policies, to identify good and bad practices and to encourage the replacement of inefficient institutions with more efficient ones. With the increasing harmonization of the banking market in the European Union, few obstacles remain (if any), leading to increased competition among financial institutions.

In recent years the effects resulting from globalization, deregulation and the sophistication of international financial systems have led to an increase in volatility and to the appearance of new financial products. These trends resulted in higher levels of risk faced by banks, when compared to the risks that these institutions traditionally bear. These changes have fostered the need for the reinforcement of prudential regulation, making financial systems more robust and able to ensure good indicators of solvency, liquidity and efficiency.

This study is motivated by the necessity to explore efficiency and its drivers. Given the competitive pressures and the reinforcement of regulation and supervision, only the most efficient banks will endure in the financial market.

The main contribution is to increase knowledge of the efficiency of banks, applying the DEA methodology and allowing comparisons between the Portuguese banks and their Spanish counterparts (as far as we know, no other study explores these two particular countries). In addition we use fractional response models, as a suitable econometric approach to explain the efficiency scores, which are proportions, and as such we try to circumvent some of the methodological limitations of past empirical applications.[1]

The plan of this paper is as follows. The next section presents a brief literature review. Section 3 explains the research methodology and the econometric approach, detailing the data. Results are presented and discussed in Sect. 4. Finally, Sect. 5 draws the main conclusions.

[1] See, for instance Hauner (2005) or Pasiouras (2008) who applied Tobit regressions.

2 Literature review

The literature on banking efficiency is very extensive. For instance, Berger and Humphrey (1997) present 130 studies on the efficiency of financial institutions, covering 21 countries, using parametric and non-parametric techniques.

The majority of the empirical papers in the financial sector applying non-parametric techniques, namely DEA, are cross-country studies.[2] Just to cite a few examples: Pastor et al. (1997); Hauner (2005); Pasiouras (2008); Chortareas et al. (2012). As noted in Berger and Humphrey (1997), cross-country comparisons are difficult to interpret because the regulatory and economic environments faced by financial institutions are likely to show important differences across nations; however, this analysis can provide valuable information about banks' competitiveness, an important issue, particularly to the European financial institutions, given the Single Market of the EU.

The present study is most closely related to the studies of Hauner (2005)—who compares the banking systems of two neighbouring countries (Germany and Austria)—and of Chortareas et al. (2012) in the two-stage approach. In a summary, Hauner (2005) explores cost efficiency, scale efficiency and productivity change among large German and Austrian commercial banks, applying DEA over the years 1995–1999. In addition, cost-efficiency was regressed on several explanatory variables. The results show that: neither cost-efficiency nor productivity improved, on average; Austrian banks were found to be significantly less cost-efficient than German banks; there appear to be significantly increasing returns to scale but returns to scope are found to be negative in the German and Austrian banking systems; and finally, no significant differences between the cost-efficiency of privately owned banks and cooperative banks were found. More recently, Chortareas et al. (2012) investigated the dynamics between key regulatory and supervisory policies and various aspects of commercial bank efficiency and performance for a sample of 22 European countries over the period 2000–2008 using a two-stage DEA method. First, efficiency was measured by DEA and in the second stage, truncated regressions were used to explain these scores and to explain two additional performance measures based on accounting ratios. The results show that strengthening capital restrictions and official supervisory powers can improve the efficiency of banks. The authors also indicate that interventionist supervisory and regulatory policies such as private sector monitoring and restricting bank activities can result in higher bank inefficiency levels.

With a focus on the Portuguese banking sector, previous empirical results on the efficiency of Portuguese banks include the studies of Camanho and Dyson (1999), Mendes and Rebelo (1999, 2001), Pinho (2001), Canhoto and Dermine (2003), Portela and Thanassoulis (2007), Lima (2008), Lima and Pinho (2008) and Martins (2009).[3]

[2] It is also possible to find papers focused on the analysis of bank branches within the same financial institution.

[3] Some of the studies focused on the analysis of bank branches with DEA: Camanho and Dyson (1999), Portela and Thanassoulis (2007).

Mendes and Rebelo (1999) performed an analysis of efficiency in the Portuguese banking sector from 1990 to 1995, applying a stochastic frontier analysis (SFA). They concluded that the increased competition that followed the entry of Portugal into the European Community did not lead to the expected increase in the efficiency levels and many banks were less efficient in 1995 than in 1990. Additionally, they concluded that efficiency and economies of scale do not seem to be related to the size of the institution.

In Mendes and Rebelo (2001) two main methods were used to measure efficiency: the Stochastic Frontier Analysis (SFA) and DEA. This study estimates the effects of mergers and acquisitions on banking sector efficiency between 1990 and 1997. The analysis of the sample, consisting of 46 banks, showed that there was an improvement in cost efficiency after privatization. Inefficiency levels in costs varied according to the estimation method used. With DEA, the average inefficiency level was 37.3 %, while with the SFA the level of inefficiency was between 9.8 and 18.2 %. Mergers simulated by the authors seem to contribute to an increase in efficiency.

According to Pinho (2001) the protectionist past in the banking sector may have resulted in low productivity and a lack of marketing strategies, mostly in the oldest banks. The reduced levels of competition that persisted in Portuguese banks until the early 90 s may have reduced the incentives for competition in costs. One of the factors that negatively influenced efficiency was the Government ownership; therefore privatization policies were very important to reduce the sector's inefficiency levels.

Canhoto and Dermine (2003) quantified the impact of deregulation on the efficiency of 20 Portuguese banks between 1990 and 1995. These authors divided the banks into two groups, new and established (old banks). They concluded that in the period under review there was an increase in efficiency of around 59 %. They also observed that the new banks recorded higher levels of efficiency than banks already established, with an average efficiency score of 77 % against 62 %.

According to Lima and Pinho (2008), the different strategies adopted by banks affect the levels of efficiency. For example, often what is first classified as inefficiency in costs may result from an additional effort to capture a larger market share (more clients) and contribute to higher profits over time, resulting in improved efficiency in terms of revenues. This study used a parametric method to analyse cost efficiency and revenue in the Portuguese banking sector between 1997 and 2004.

Martins (2009) assessed the efficiency of the 37 major banks operating in Portugal in 2007, via DEA in a two-stage model, using the production and intermediation approach. In this study, beyond the general analysis, an analysis by groups was carried out, taking into account the differences in size/business and risk level. The main findings show that most of the studied banks have very low efficiency levels, banks with higher value creation were more efficient in the intermediation, and larger banks were more efficient concerning profitability.

About efficiency in Spanish banks, some frontier studies include Grifell et al. (1992), Pastor (1994), Pastor et al. (1997), Lozano-Vivas (1997), Tortosa-Ausina (1999), Maudos and Pastor (2003), Tortosa-Ausina et al. (2008), and Leire et al. (2014).

Pastor et al. (1997) compared the Spanish banks with the banking systems of different European countries and the USA. The results revealed that the most efficient banking systems were France, Spain and Belgium, whereas the UK, Austria and Germany showed the lowest efficiency levels.

Lozano-Vivas (1997) determines how deregulation has affected the profit efficiency of Spanish savings banks over 1986–1991 (a period in which the Spanish banking industry saw considerable deregulation), using the thick frontier approach. The results revealed that the identification of best-practice and worst-practice firms is not likely to be the result of luck or transitory influences but rather reflect the influence of persistent differences in efficiency. The profit inefficiency measured here, which includes both cost and revenue inefficiencies, is more than twice as large as the cost inefficiency, measured for the same set of savings banks over the same time period. This suggests that revenue inefficiencies may be larger than cost inefficiencies for Spanish savings banks.

Tortosa-Ausina (1999) investigates productivity growth and productive efficiency for Spanish savings banks over the (initial) post-deregulation period 1992–1998 using DEA and bootstrapping techniques. Results show that productivity growth has occurred, mainly due to improvement in production possibilities, and that mean efficiency has remained fairly constant over time.

Maudos and Pastor (2003) analysed cost efficiency and profit efficiency in the Spanish banking market in the period 1985–1996, with DEA. These authors analysed the efficiency of both the cost and the revenue side. The results show the existence of profit efficiency levels well below those corresponding to cost efficiency. Cost efficiency, on average, for the Spanish Banks and *Cajas de Ahorros*, was 80.2 % and 90.9 %, respectively.

Tortosa-Ausina et al. (2008) consider that during the last 15 years the competitive conditions under which Spanish banking firms operate have become much tighter, with the effects of deregulation. This paper analyses how, in these circumstances, banking efficiency has been affected using DEA. Results differ depending on the output definition, but regardless of the definition considered, efficiency scores were more dispersed in 1985 and more concentrated in 1995.

Leire et al. (2014) contribute to qualify the magnitude of social and economic efficiency of the Spanish savings banks, over the period 2000–2011, using a two-stage approach: DEA and a Tobit model combined with bootstrapped tests. The data covers the period of financial banking crisis, which has increased pressures on financial entities to operate more efficiently. The main results obtained revealed that Spanish savings banks are not less efficient globally than other banks, but are more efficient socially.

3 Methodology

Performance and efficiency are difficult to measure. Concerning banks' performance, accounting ratios were extensively used. Just to cite one example, Hanafi et al. (2013) use accounting measures to explore risk and profitability in the Indonesia's banking sector over the period 2002–2008. More recently, several methods to estimate efficiency have been developed, which can be classified into two main groups: parametric (namely, Stochastic Frontier Approach—SFA, Distribution Free Approach—DFA) and non-parametric (Data Envelopment Analysis—DEA). The main difference between parametric and non-parametric methods relies on the assumptions about the random errors and on the underlying distribution. While the parametric approaches have the advantage of decomposing deviations between "noise" and pure inefficiency, the non-parametric approaches classify the whole deviation as inefficiency, but otherwise they have the advantage of not imposing a particular parametric functional form, avoiding misspecification errors.

Berger and Humphrey (1997) mention that bank efficiency studies use interchangeably parametric and non-parametric approaches, without a clear superiority of one approach over the other, although the choice of the method significantly affects the efficiency level results. All in all, efficient frontier approaches for measuring performance seem to be superior when compared to the use of traditional financial ratios from accounting statements [e.g. return on assets (ROA) or the cost to revenue ratio], providing an overall objective numerical score. In this empirical analysis, we choose to use DEA to first estimate the efficiency scores of the Portuguese and Spanish banks.

DEA is based on the idea of technical efficiency, measured by the ratio of output to input. It allows the identification of the efficient and inefficient units in a comparison of each unit with its peers (within the group).[4] This programming technique was first developed by Charnes et al. (1978) and since then it has been used to assess efficiency in areas such as health, prisons, courts, schools and universities and more recently, transit and banking. Initially DEA was used in microeconomic settings, but its popularity led to an extension to the macroeconomic level, for instance, to measure the efficiency of governments (see for more details, Wang and Alvi 2011).

The efficiency scores obtained with constant returns to scale (CRS) indicate the overall technical efficiency (OTE). The use of variable returns to scale (VRS), following Banker et al. (1984), allow us to decompose the OTE into a product of two components:

$$OTE = PTE \times SE$$

where

- PTE is pure technical efficiency obtained under VRS and relates to the ability of managers to use firms' resources. These scores are higher than or equal to those obtained under CRS;
- SE is scale efficiency and refers to exploiting scale economies and measures whether a bank produces at an optimal size of scale. SE is obtained by dividing OTE by PTE.

[4] For more details on the DEA methodology, see for instance, Ray (2004).

DEA is a potential tool to access the relative performance of homogeneous units.[5] It compares the relative performance of each decision making unit (DMU) with the "best" performance. The advantages of DEA include its ability to accommodate a multiplicity of inputs and outputs; there is no need to specify a particular functional form for the production frontier, and no prior establishment of rules for the weights is necessary. In addition, it works particularly well with small samples. By contrast several limitations may be pointed out, namely: the assumption that there is no random error (any deviation from the estimated frontier is considered inefficiency); the results' sensitiveness to the selection of inputs and outputs; it is not possible to test for the best specification; and the number of efficient DMU on the frontier tends to increase with the number of input and output variables. As a rule of thumb, it is usually required that the number of DMU should triplicate the number of variables.

In the second stage, we regress the efficiency scores of the first stage, against several potential explanatory variables—bank specific attributes, country-specific and institutional variables. The efficiency scores are proportions, therefore classified as a fractional response variable, ranging from 0 to 1. We use the generalized linear models (GLM) approach, first proposed by Papke and Wooldridge (1996), with clustered robust standard errors. Several functional forms for the conditional mean of y that enforce the conceptual requirement that $E(y|x)$ is in the unit interval, may be used. We have,

$$E(y|x) = G(z)$$

where $\mathrm{G}(\cdot)$ is a known nonlinear function satisfying $0 < \mathrm{G}(\cdot) < 1$. While the logistic and standard normal specifications for $\mathrm{G}(\cdot)$ are symmetric about the point 0.5 and consequently approach 0 and 1 at the same rate, the Complementary Loglog model is not symmetric and increases sharply when $\mathrm{G}(\cdot)$ is near 1, making this latter model the more appropriate to fit our data.[6] The estimated scores verify $0 < \mathrm{y} \leq 1$, with a large proportion of observations close to $\mathrm{y} = 1$.

Here, it is important to stress that traditional linear models or Tobit approaches to second-stage DEA analysis do not constitute a reasonable data-generating process for DEA scores, as pointed out by Ramalho et al. (2010). Under the assumption that DEA scores can be treated as descriptive measures of the relative performance of units in the sample, fractional regression models are the most natural way of modelling bounded, proportional response variables such as DEA scores.

3.1 Model specification and variables

There are two different approaches concerning modelling bank activities: the "production approach", modelling banks as using labour and physical capital to

[5] We may consider Portuguese and Spanish banks homogeneous units, because they share the same business model and although the analysis is focused on two different countries, the banking systems are similar with some of the banks operating in Portugal being owned by Spanish institutions (for instance, Totta, Popular, BBVA).

[6] For a detailed analysis of fractional response models see Ramalho et al. (2011).

produce services for account holders and, the "intermediation approach", developed by Sealey and Lindley (1977), where banks are seen just as intermediaries between savers and investors. The right choice of the inputs and outputs is critical for the DEA model. Following similar works on banking and adopting the intermediation approach, where banks are intermediaries receiving deposits and providing loans, we adopt as inputs: personnel expenses and deposits and, an output: loans.

Given the small dimension of the sub-samples, 12 banks in Portugal and 14 banks in Spain, it was not possible to use a higher number of input/output variables. Moreover, it is the small number of banks in Portugal that motivates the choice of the non-parametric approach.

For the DEA model we assumed an input orientation, meaning that the model searched the minimization of inputs for the given level of outputs. This option seems to be appropriate for the banking sector, given the pressure to control costs.[7] The same applies in different sectors, like transport or health, where the focus is on the control of the operational costs. In addition, DEA results are presented assuming CRS and VRS.

For the regression framework, in the second stage, several bank and country-specific variables were tested as independent variables to explain the efficiency scores, following similar works (among others, Hauner 2005; Pasiouras 2008; Chortareas et al. 2012). We consider as,
Bank-specific variables:

- *liquidity*, assessed by the ratio of total loans to total deposits—*l2dep*;
- *capitalization*, measured by the ratio of equity to total assets—*equity2ta*—and controls for capital strength;
- *size* measured by the natural logarithm of banks' total assets—*TA (ln)*;
- Z-score to measure the *risk of insolvency*. This score is estimated as (ROA + equity/assets)/sd(ROA)—*zscore*—and represents the volatility of a bank's return on assets (ROA). Lower values of the Z-score are associated with higher probabilities of failure. Empirical studies tend to find a significant relationship between banks' risk and performance (e.g. Konishi and Yasuda 2004; Stiroh, 2004).
- *State owned*—Dummy = 1 for government-owned banks (as opposed to private ownership);
- *Spanish*—Dummy = 1 for Spanish banks;
- *Not foreign*—Dummy = 1 for banks not controlled by a different country.

Favourable economic conditions will affect positively the demand for banking services, and will possible improve bank efficiency, for instance Maudos et al. (2002) find that banks that operate in expanding markets (with higher growth rates of GDP) present higher levels of profit efficiency. Control of corruption and the level of financial development are also important drivers of the performance of financial institutions. Kasman and Yildirim (2006) find that overall financial

[7] The other possibility was to choose output orientation, where the goal is to maximize outputs maintaining the level of inputs constant.

development measured by banking market size and levels of monetarization and capitalization contributes to higher efficiency.

Country-specific and institutional variables:

- *GDP_pc growth*—gross domestic product per capita growth, to measure the impact of the macroeconomic environment on the banks' operations—*gdp_pc*—obtained from the World Development Indicators (WDI);
- *control of corruption*—drawn from Kaufmann et al. (2010). It reflects perceptions of the extent to which public power is exercised for private gain, including petty and grand forms of corruption, as well as "capture" of the state by elites and private interests. It ranges from approximately −2.5 (weak) to 2.5 (strong) governance performance—*Corruption*—larger values indicate better control of corruption by government officials;
- *financial development* is measured by claims on the domestic real nonfinancial sector by deposit money banks as a share of GDP and provides the relative importance of the services provided by financial institutions—*dbagdp*—drawn from the World Bank financial structure database of Beck et al. (2009).

3.2 Data

The dataset used to perform the DEA analysis consists of individual bank data drawn from BankScope by Bureau van Dijk. We focus on commercial, savings and investment banks, excluding cooperative institutions, due to their type of ownership. Cooperative banks may have different goals than profitability or cost reduction in operational terms. Therefore we considered the available data on commercial, savings and investment banks in the assumption that all have access to the same technology and share the same business model.

To perform the regression analysis in the second stage, we use two different groups of explanatory variables. The data source for the bank-specific characteristics is BankScope. For the second group, including country-specific factors and institutional variables that are expected to influence banks' efficiency, we use information from WDI, Beck et al. (2009) and Kaufmann et al. (2010).[8]

4 Empirical results

4.1 First-stage DEA results

All the results were obtained using STATA 12 statistical software. Concerning DEA, the efficiency scores are estimated using data on each country separately, and then using the full sample, for the period of 2008 until 2013.[9]

[8] Database available at http://info.worldbank.org/governance/wgi/index.aspx#home.

[9] A DEA analysis of banks in Portugal and Spain was first performed with separate frontiers for each country and then with a "common" frontier.

Table 1 Efficiency scores (OTE) average by country and year

	2008	2009	2010	2011	2012	2013	Average
Portugal (N = 12)	0.719	0.781	0.813	0.799	0.802	0.737	0.775
Spain (N = 14)	0.876	0.869	0.817	0.871	0.764	0.813	0.835

OTE overall technical efficiency under constant returns to scale

4.1.1 Country results

The banking sector in the Iberian Peninsula has evolved in the last decades subject to a series of structural changes in the market. The key reforms were deregulation, liberalization, conformation to the new community laws, homogenization of the business model of banks and *Cajas de Ahorros* (Spanish savings banks), freedom of establishment and adoption of new and innovative technologies. The late nineties witnessed the end of an expansionist phase. Mergers occurred derived from the necessity to rationalize operations, to reduce costs and also influenced by the increasing use of electronic operations.

More recently, with the financial crisis Portugal was forced to request international financial assistance from the European Union and the International Monetary Fund. The intervention of the Troika[10] in Portugal, from May 2011 until May 2014, imposed several measures to reinforce the stability of the financial system. Particularly in the banking system, these measures included the reinforcement of liquidity, the increase of capital ratios and the strengthening of regulation and supervisory powers. Likewise, the banking sector in Spain was affected by the financial crisis. In November 2012, four Spanish bank groups needed Government intervention to ensure their viability and the stability of the overall financial system. This first wave of banks was composed by Bankia, Catalunya Caixa, Novagalicia Banco and Banco de Valência, which used capital from the Fondo de Reestructuración Ordenada Bancaria (FROB). In the first phase, the FROB functions were to improve capital levels and to manage the restructuring processes of Spanish financial institutions (FMI 2012).

Following these measures and given our period of analysis, we expect efficiency levels of the financial institutions to be affected. Table 1 shows the average OTE scores by year and by country.

For the full sample of the 12 Portuguese banks the average OTE score is 77.5 %, which means that the average bank in the sample could have achieved the same outputs, using only 77.5 % of the inputs. In addition, it is possible to see that after an increasing trend from 2008 until 2010, the year of 2011 effectively marks a decline. In 2012, there is a small recovery in the OTE average but followed by a new decline in 2013. Comparing these results with those of Canhoto and Dermine (2003), who found an efficiency score of 69 % (average OTE) for the total sample of Portuguese banks in the period 1990–1995, we may conclude that there was an improvement in the banks' efficiency level over time.

[10] In May, 2011 the Portuguese Government signed the Memorandum of Understanding with the Troika (the European Commission, the European Central Bank and the International Monetary Fund).

Table 2 Detailed DEA results for the Portuguese banks

Bank	Ranking	Average	Max	Min
BBVA	1	0.958	1.000	0.828
Montepio	2	0.948	1.000	0.819
Totta	2	0.948	1.000	0.886
BCP	3	0.891	0.984	0.827
BES	4	0.859	0.949	0.769
CGD	5	0.844	0.965	0.739
BANIF	6	0.840	0.923	0.747
BPI	7	0.809	0.896	0.698
Popular	8	0.788	1.000	0.855
BIC	9	0.714	1.000	0.469
Finantia	10	0.450	0.715	0.259
BIG	11	0.132	0.242	0.047
ALL	–	0.775	0.813	0.719

Six-year average scores (OTE)

For the Spanish banks, the average OTE is 83.5 %. This result, although for a different period, is consistent with the results of Maudos and Pastor (2003)—who reported average levels of cost efficiency of 80.2 % and 90.9 %, respectively for Spanish banks and *Cajas de Ahorros*—and seems to show an improvement. Over time, the average scores exhibited a decreasing trend from 2008 until 2010, and recovering in 2011 but with a minimum in 2012, the year with more financial turmoil in the Spanish banking market. In 2013, some evidence of recovery is highlighted.

Detailing the results for the individual banks in the sample, Table 2 presents the OTE scores for the Portuguese institutions.

Given the average of the OTE for the six-year period, the most efficient institutions are BBVA, Montepio and Totta, with efficiency levels above 90 %. Notably two of these banks are foreign-owned, namely by Spanish banks. CGD, the government-owned bank, appears in 5th place, performing better than private institutions like BPI, but behind BCP or BES. It is worth mentioning that the small size of the banks BIG and Finantia makes them outliers, and therefore they were excluded from the following analysis.[11]

Individual bank results for the Spanish institutions are presented in Table 3.

The sample includes banks and *Cajas de Ahorros* and two institutions that underwent intervention by the FROB, Banca Financeira Bankia (since June of 2012) and Mare Nostrum, SA (since January 2013). Excluding these banks that had Government intervention, all the Spanish banking system is privately held.

Given the average of the OTE for the six-year period, the most efficient institutions are Bankinter, SA, B. Financeira Bankia, Sabadell, SA and Monte Piedade, Zaragosa with efficiency levels above 90 %. Surprisingly, Bankia appears

[11] Despite their exclusion, they do not affect the ranking and the average score of each bank of Table 2, because DEA compares each bank with its peers. The benchmark is BBVA and we are excluding the last two banks in the ranking.

Table 3 Detailed DEA results for the Spanish banks

Bank	Ranking	Average	Máx	Mín
Bankinter,_SA	1	1.000	1.000	1.000
B__Financ__Bankia	2	0.933	1.000	0.800
Sabadell,_SA	3	0.912	0.971	0.862
Monte_Piedad_Zar_	4	0.910	1.000	0.767
Kutxabank,_SA	5	0.893	0.994	0.835
Mare_Nostrum,_SA	6	0.889	1.000	0.695
Liberbank,_SA	7	0.875	0.961	0.791
Unicaja,_Ronda_Cádiz	8	0.845	0.950	0.745
Caja_Ahorros_Barc	9	0.839	1.000	0.731
Deutsch_Bank,_SAE	10	0.781	0.936	0.668
Santander	11	0.742	0.812	0.681
Bilbao_Vizcaya	12	0.716	0.753	0.687
Banca_March,_SA	13	0.691	0.841	0.575
Caja_3	14	0.686	0.823	0.525
ALL	–	0.835	0.876	0.764

Six-year average scores (OTE)

Table 4 Efficiency scores (OTE) average by country and year

	2008	2009	2010	2011	2012	2013	OTE
Full sample							
All banks	0.794	0.820	0.818	0.847	0.747	0.784	0.802
Portugal	0.772	0.821	0.819	0.813	0.726	0.743	0.783
Spain	0.807	0.819	0.817	0.871	0.762	0.813	0.815

OTE overall technical efficiency under constant returns to scale

in 2nd place, indicating that apparently, efficiency levels are not directly related to capital requirements.

4.1.2 Global results: comparing bank efficiency

In this section, we compare the full sample of Portuguese and Spanish banks, comparing each institution with its peers. Results are exhibited in Table 4.

The average efficiency score of Portuguese and Spanish banks for the 144 observations over the years 2008–2013 was 0.802. Comparing the results, using the full sample of the Portuguese and Spanish banks, it is possible to see that on average the Spanish institutions exhibit higher efficiency scores (OTE) in every year, with the exception of 2009 and 2010, with an average for the 6-year period of 81.5 % (3.2 percentage points above the Portuguese average of 78.3 %). In addition, for the Portuguese banks in the sample and comparing with their Spanish counterparts there is some evidence of deterioration in efficiency over the last years.

Using simple comparisons, the results appear to be not significantly different, which could be explained by the similarities in the financial markets between these

Table 5 Detailed DEA results (average by country)

	OTE	PTE	SE
All banks (N = 24)	0.8016	0.8854	0.9053
Portugal (N = 10)	0.7825	0.8745	0.8948
Spain (N = 14)	0.8150	0.8934	0.9122

Country means are calculated by averaging the scores obtained from the common frontier

OTE overall technical efficiency under constant returns to scale, *PTE* pure technical efficiency under variable returns to scale, *SE* scale efficiency

countries. Therefore, we compute a two-group mean comparison test, achieving -1.61 (p value of 0.1077) and as such, not rejecting the null hypothesis at 10 % level, i.e., there is no statistically significant difference between the average OTE scores of the two countries. However, this is not a strong result with a p-value of only 0.1077.

Table 5 provides the breakdown of the OTE scores, splitting the overall score into PTE and SE. It should be emphasized that these scores are an average by country, for the period 2008–2013, obtained from a common frontier.

The mean OTE and PTE for all banks in the sample equal 0.8016 and 0.8854 respectively, resulting in an average SE of 0.9053. Hence the average bank in the sample could improve its overall technical efficiency by approximately 20 % and pure technical efficiency by 11.46 %. That is, the sample banks could on average have produced the same level of outputs with only 80 % (or 89 % under VRS) of the inputs currently being used. The mean SE score indicates that the sample banks deviated 9.5 % on average from their efficient size of scale. The more efficient country appears to be Spain with OTE and PTE equal to 0.8150 and 0.8934 respectively. In relation to the size of scale, banks operating in Portugal are the more inefficient which deviates from the efficient size by 10.52 %.

4.2 Second-stage regression results

In the second stage of the analysis, we investigate the determinants of efficiency by using a fractional response model to explain the overall technical efficiency scores (OTE) obtained in the first phase. The estimations were conducted using STATA 12 and the full sample of 24 banks, covering the period of 2008–2013, in a cross-sectional regression. As the first step, a collinearity test was performed using the VIF (variance inflation factor) measure available in STATA,[12] with no problems identified. Table 6 presents the regressions results, with four different specifications of the Fractional Cloglog model using GLM (generalized linear models) and quasi-maximum likelihood estimation.

Model 1 presents the results of the full sample of banks, models 2 and 3 are two separate regressions, one for each country and in model 4, we add the dummy

[12] VIF is an indicator of how much of the inflation of the standard error could be caused by collinearity. As a rule of thumb, values above 10 should be a cause of concern and must be corrected.

Table 6 Regressions results

Dependent variable	Fractional Cloglog model			
Efficiency score (OTE)	(1)	(2) Portugal	(3) Spain	(4)
Liquidity	2.071***	1.766***	2.381***	1.766***
	(8.39)	(8.28)	(14.84)	(8.32)
Capitalization	−0.198	0.422*	−0.978***	0.422*
	(−0.56)	(1.90)	(−2.61)	(1.91)
Size	−0.000	−0.038	−0.019	−0.038
	(−0.01)	(−1.43)	(−1.35)	(−1.44)
Risk (zscore)	−0.016	0.027	−0.044***	0.027
	(−1.16)	(1.63)	(−4.78)	(1.64)
GDP_pc growth	0.019***	0.022	0.008	0.022
	(59.35)	(1.26)	(0.58)	(1.26)
Financial Develop.	0.006***	0.007***	0.001	0.007***
	(8.61)	(4.32)	(0.28)	(4.35)
Stateowned	−0.017	−0.057	0.322	−0.057
	(−0.31)	(−1.44)	(1.17)	(−1.45)
Notforeign	−0.290	−0.425***	0.155***	−0.425***
	(−1.08)	(−6.11)	(2.93)	(−6.14)
Corruption	−0.971***	−0.546	−1.112***	−0.546
	(−4.35)	(−1.09)	(−3.51)	(−1.09)
Spanish				1.986**
				(2.00)
SpanishLiquidity				0.615**
				(2.31)
SpanishCapital				−1.400***
				(−3.23)
SpanishSize				0.019
				(0.62)
SpanishZscore				−0.071***
				(−3.77)
SpanishGDP_pc				−0.014
				(−0.61)
SpanishFinanDev				−0.006**
				(−2.11)
SpanishStateowned				0.379
				(1.37)
SpanishNotforeign				0.580***
				(6.66)
SpanishCorruption				−0.565
				(−0.96)
Constant	−1.360***	−1.907***	0.080	−1.907***
	(−20.85)	(−3.54)	(0.10)	(−3.55)

Table 6 continued

Dependent variable	Fractional Cloglog model			
Efficiency score (OTE)	(1)	(2) Portugal	(3) Spain	(4)
Number of observations	142	59	83	142
Correlation (y yhat)^2 (%)	66.39	80.25	82.28	81.76
Linktest (p-value of hatsq)[a]	0.914	0.077	0.749	0.130

Robust *t* statistics in parentheses (Clustered robust for model 1)

y observed values, *yhat* fitted values (prediction), *hatsq* prediction squared

* Statistically significant at 10 % level, ** at 5 % level, *** at 1 % level

[a] Linktest is a STATA routine that performs a test for model specification, providing a means of assessing adequacy for the relationship between outcome and predictors. If the model is correctly specified, then the prediction squared should have no explanatory power. The linktest performed show no evidence of misspecification problems, except for model 2, concerning Portuguese banks—this could be due to the small sample (N = 59)

variable Spanish and nine interaction terms based on Spanish to allow a model where the intercept and all slopes can be different across the two countries.

Performing a Chow test, comparing models 1 and 4, in order to ascertain if there is any difference between Portugal and Spain, concerning the determinants of bank efficiency (measured by the OTE scores), we conclude that we do not reject the null hypothesis (p-value of 0.9975), i.e., that all the coefficients on the dummy and related interactions terms are zero The same conclusion and identical p-value is achieved if we compare the full model (1), with the two sub-sets of the data—Portugal (2) and Spain (3), the other possibility to perform the Chow test.

Detailing the results, concerning bank-specific variables in the full model (1), neither size nor capitalization are relevant in explaining differences in the efficiency scores. More important appears to be liquidity (measured as total loans over total deposits), which is statistically significant in all specifications. More liquidity has a positive effect on overall efficiency scores, as expected. However, capitalization displays opposite signs for Portugal and Spain. For the Spanish banks it appears that higher capital requirements are related with lower efficiency levels. Another unexpected result is related to the z-score, although only statistically significant for the sub-sample of the Spanish banks. Risk measured by the volatility of a bank's return on assets (ROA) displays a negative sign. The higher the z-score (and lower the probability of bankruptcy), the lower the efficiency scores. According to Hauner (2005), it is often argued that efficiency should be negatively related to the risk incurred by a bank, as risk management creates administrative costs.

Consideration of the macroeconomic and institutional variables reveals that the level of financial development is a statistically significant determinant of the level of efficiency (except for the sub-sample of the Spanish banks), with more developed financial markets increasing the complementary effects between equity and debt financing and improving the operations of banks, as mentioned in Pasiouras (2008) and Chortareas et al. (2012). GDP per capita growth only appears significant in the full model—the demand for financial services can be expected to suffer with the level of economic activity. Surprisingly, control of corruption is negatively associated with efficiency levels (only relevant in model 1 and 3), in what appears to indicate that the control of corruption affects negatively the efficiency levels.

In respect to the dummy variables tested, there is no apparent distinction concerning the bank's ownership (state-owned or private) and foreign banks exhibit higher efficiency scores than domestic institutions for the sub-sample of Portuguese banks, although the opposite effect is expected for the Spanish institutions.[13]

5 Conclusions

The majority of studies about bank performance and efficiency rely on accounting measures. More recently, new approaches have been developed using frontier analysis to compute measures of bank performance. In this empirical investigation we use DEA to compute measures of the relative efficiency of Portuguese Banks, in the period of 2008–2013, comparing the results with their Spanish counterparts. In the second stage, we regress the efficiency scores on several potential explanatory variables (bank-specific and macroeconomic and institutional variables).

Several important and interesting findings are reported in this study. In general, Spanish banks are slightly more efficient than Portuguese institutions, with an Overall Technical Efficiency (OTE) average of 81.5 % against 78.3 %. The results obtained revealed that Pure Technical Efficiency (PTE) is higher than the global efficiency score, which is a sign of scale inefficiencies in several banks. This is more evident for the Portuguese banks, which gives support for further Mergers & Acquisitions. Additionally, given the financial crisis period under analysis, our results suggest that efficiency levels were affected by the Government and Troika interventions in the market.

In the second stage, explaining the efficiency scores, liquidity is particularly important as far as bank characteristics are concerned. Institutional variables like the level of financial development of a country and the control of corruption are important factors explaining efficiency, although not always displaying the expected signs. However these results should be interpreted with caution, given the small dimension of the samples. All in all, searching for structural differences between the two countries, the Chow test indicates that no statistically significant differences exist and the determinants of efficiency are similar across countries.

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[13] It is important to note that this could be due to the fact that the majority of foreign banks in the sample are Spanish banks operating in Portugal and the Spanish institutions are slightly more efficient as already noted.

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