Cost and revenue efficiency in Spanish banking: What distributions show

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Abstract

The literature analyzing the efficiency of financial institutions has evolved rapidly over the last twenty years. Most research has focused on the input side, analyzing either cost, input technical efficiency or input allocative efficiency, whereas comparatively fewer studies have examined the revenue side. However, both sides are relevant when evaluating banks' performance. This article explicitly explores how serious it may be to confine the analysis to one side of banks' activities only, comparing the efficiencies yielded by either minimizing costs or maximizing revenues. We focus on the Spanish banking sector, which is currently undergoing a profound process of change and restructuring. The application shows how severely biased the analysis is when only a partial efficiency measurement is conducted. It also shows the growing relevance of the issue since the beginning of the financial crisis.

Keywords: bank, cost efficiency, distribution, revenue efficiency

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1. Introduction

The literature on bank efficiency and productivity has expanded dramatically since the early eighties, and continues to flourish today. The amount of research has already warranted two surveys (Berger and Humphrey, 1997; Fethi and Pasiouras, 2010). Since the publication of the latter, further empirical evidence has been made available, partly due to the substantial restructuring of the banking industries in several Western economies since the onset of the international financial crisis in 2007. Under these renewed circumstances, the question of how banks' efficiency is being affected naturally arises or, perhaps more interestingly, calls for an analysis of the links between pre-crisis and crisis efficiency levels.

According to the survey by Berger and Humphrey (1997), most studies on the efficiency of financial institutions confined their analyses to either (input) technical or cost efficiency—or both. Out of the 130 studies surveyed, only nine focused on profit efficiency. However, as Berger et al. (1993b) state, these efficiencies may be much more relevant than expected. Indeed, except for the study by Miller and Noulas (1996), profit inefficiencies have generally been found to be larger than those attributable to the failure to minimize costs. Much more recent surveys such as Fethi and Pasiouras (2010) also corroborated this sort of unbalance in the literature, since their study, which covered studies employing operational research and artificial intelligence techniques to assess bank performance, corroborated the relative absence of studies analyzing either profit or revenue efficiency in banking.

This type of inefficiency is important for several reasons. First, we recall that banks attempt not only to offer products and services at the minimum cost—i.e., to be cost efficient—but also to maximize the revenues they generate—i.e., to be revenue efficient. Together, both attempts imply profit efficiency. By omitting the revenue side, we provide a partial, and probably misleading, view of bank performance, although some relatively recent initiatives such as Cuesta and Orea (2002), Rezitis (2008) and Feng and Serletis (2010) have attempted to fix this gap in the literature, by considering output orientations. We will expand further on this below.

The scarce empirical evidence adds to the higher quantitative relevance of assessing profit inefficiency relative to cost inefficiency, suggesting significant inefficiencies on the revenue side, either due to a wrong output mix—given output prices—or the setting of an inadequate price policy. Some studies that estimate both profit and cost inefficiency, such as Berger and Mester (1997) concluded that the first type of inefficiency is always lower—see also Maudos and Pastor

(2001), who focus on an international sample. In addition, as Berger and Mester (1997) suggest, and contrary to what one might *a priori* expect, profit (and/or revenue) efficiency and cost efficiency are not always positively correlated, and they could even be *negatively* correlated. In such circumstances, the most cost inefficient banks could offset this apparent inefficiency by adopting different paths such as raising higher revenues than their competitors through their output mix, or exploiting stronger market power when setting prices. Berger and Mester (1997) refer to the situation in which market power exists in fixing output prices as alternative profit efficiency.[1] In contrast, if output prices are given, they use the concept of standard profit efficiency.

Therefore, cost inefficiency might also include some costs that should be attached to a bank's product mix. Accordingly, one should consider the possibility that some specializations are more costly than others, which does not necessarily entail their being more inefficient. Estimating profit or revenue efficiency might capture this specialization effect. Higher revenues could therefore offset the higher costs of firms that emphasize more expensive product lines.

This article attempts to measure both sides of inefficiency, i.e. cost *and* revenue, by applying Free Disposal Hull (FDH) (Deprins et al., 1984; Diewert and Fox, 2014) the *non-convex* variant of one of the most popular linear programming methods considered to measure bank efficiency, namely, Data Envelopment Analysis (DEA) (Charnes et al., 1978). Although some authors such as Briec et al. (2004) have argued convincingly about the advantages of using non-convex methodologies (such as FDH) as opposed to convex methods (such as DEA), in certain contexts such as Spanish banking (on which we focus) the empirical evidence available so far has completely disregarded non-convex technologies.

Relatively few studies such as those by Färe et al. (2004), Devaney and Weber (2002), and Maudos and Pastor (2003) have used linear programming techniques (either DEA or FDH) to measure profit efficiency. If the analysis is confined to revenue efficiency, the existing literature on applications to the banking sector is rare, but existent (Cuesta and Orea, 2002; Rezitis, 2008; Feng and Serletis, 2010). In contrast, the number of studies that have analyzed bank profit efficiency using econometric techniques is remarkably higher. Among them, and apart of some of

[1] In a slightly previous application, Berger et al. (1996) had evaluated revenue economies of scope, considering an alternative specification for the revenue function in which banks were known to have some control over the level of output prices charged. This view was also adopted by Humphrey and Pulley (1997). However, later on Khumbhakar (2006) and Restrepo-Tobón and Kumbhakar (2013) proposed to estimate the so-called Composite Non-Standard Profit Function (CNSPF), due to some advantages over non-standard profit efficiency approaches. We thank an anonymous referee for this clarification.

the contributions cited above, we should also include in this group the studies by Berger et al. (1993a), DeYoung and Hasan (1998), Maudos et al. (2002), Isik and Hassan (2002), Vander Vennet (2002) and, more recently, Pasiouras et al. (2009), Srairi (2010), Lozano-Vivas and Pasiouras (2010) and Akhigbe and McNulty (2011), among others. However, some contributions have still been added to the field of nonparametric profit efficiency measurement. In this (much smaller) group, we find recent theoretical work from Fu et al. (2016) and Cherchye et al. (2016), and, from a more applied perspective, Ray and Das (2008) and Ariff and Luc (2008).

Our analysis focuses on Spain, which has one of the largest banking systems in Europe. It offers a scenario where profound changes have taken place such as interest rate deregulation, partial or total removal of legal coefficients, legal homogenization of both commercial and savings banks, free entry for European Union banks (as long as they comply with European Union legislation), removal of the restrictions on the geographical expansion of savings banks, implementation of new telecommunications technologies, etc. However, interest in analyzing this banking system has grown mainly as a result of the current scenario of international economic and financial crisis, which is having a severe effect on the Spanish economy and its financial institutions in particular. Although several euro-area countries are now under strain, the difficulties of the Spanish financial system are particularly worrying because of its size.

In this line, although international investors are increasingly concerned about the various performance measures for Spanish banks, a rigorous performance analysis such as an accurate measurement of efficiency using state-of-the-art methods may provide some valuable information that goes beyond that of the rating agencies. More specifically, in this restructured industry, in which financial institutions are adapting to the new macroeconomic and regulatory scenario, analyzing bank efficiency is gaining momentum, partly because of the alleged inverse relationship between competition and inefficiency or, more precisely, X-inefficiency (Leibenstein, 1966, 1978a,b).[2] Most empirical analysis of the competitive viability of Spanish banking firms took place in the 1990s and early 2000s when deregulatory initiatives were having their effects on banks. However, to a large extent these research studies focused overwhelmingly on cost aspects, or even on a particular component of cost efficiency (technical efficiency).

More specifically, some previous studies estimated the effects of the deregulation process

[2]However, Stennek (2000) casted some doubt on the validity of X-inefficiency as a survival condition in a competitive environment.

on the efficiency of Spanish savings banks, such as Grifell-Tatjé and Lovell (1996), Lozano-Vivas (1997), or Kumbhakar et al. (2001). However, others included both commercial *and* savings banks in the analysis; see, for instance, Grifell-Tatjé and Lovell (1997), Tortosa-Ausina (2002a,b,c, 2003) or Carbó Valverde et al. (2007), among others. By comparison, the number of studies analyzing the the efficiency of Spanish credit unions is much lower, with very few exceptions such as Marco Gual and Moya Clemente (1999) and, more recently, Grifell-Tatjé and Lovell (2004) and Grifell-Tatjé (2011), none of which focus explicitly on revenue efficiency.

This paper differs from the previous literature in that we perform an efficiency analysis for Spanish banking covering a very recent period including both pre-crisis and crisis years (important because of the major effect the crisis is having on the Spanish economy in general and the Spanish financial system in particular); it includes commercial banks, savings banks and credit unions (relevant because of the way the crisis has different effects on the different organizational forms); it examines both cost and revenue efficiency; and it considers Free Disposal Hull (FDH), the non-convex variant of Data Envelopment Analysis (DEA) which, as far as we know, has not been previously applied to the particular case of Spanish banking. In this particular regard, the studies that have examined either profit or revenue in Spanish banking are scant, boiling down to Lozano-Vivas (1997), Maudos and Pastor (2003) and, to a lesser extent, Cuesta and Orea (2002).

The study proceeds as follows. The next section (section 2) presents the methodology used to measure cost and revenue efficiency. Section 3 describes the data and the specification of banking inputs and outputs. Section 4 presents the results. Finally, section 5 outlines some concluding remarks.

2. Methodology

Most of the literature related to the measurement of economic efficiency has based its analysis either on parametric or nonparametric frontier methods. As Murillo-Zamorano (2004) indicates in his survey paper, the choice of estimation method has been an issue of debate, with some researchers preferring the parametric, and others the nonparametric approach (Murillo-Zamorano, 2004, p.33).

Efficiency measurement involves a comparison of actual with optimal performance located on the relevant frontier but, since the true frontier is unknown, an empirical approximation is needed. This approximation is frequently dubbed a "best-practice" frontier (Fried et al., 2008, p.32). However, as Berger and Humphrey (1997) suggest when inquiring whether a "best" frontier method exists, "the lack of agreement among researchers regarding a preferred frontier model at present boils down to a difference of opinion regarding the lesser of evils".

On the one hand, the parametric approaches fail when they impose a particular functional form that presupposes the shape of the frontier—hence, if the functional form is misspecified, measured efficiency may be mixed up with the specification errors. On the other hand, nonparametric methods impose less structure on the frontier but fail because they de not allow sufficiently for random error (due to either luck, measurement errors, etc).[3]

Some research studies have analyzed financial institutions' efficiency using both parametric and nonparametric methods. In some, correlations between the two approaches are extremely low, and negative. In others, the opposite result is achieved. Chronologically, Ferrier and Lovell (1990) compared efficiency scores yielded by econometric and linear programming techniques, and found statistically insignificant Spearman correlation coefficients of 0.0138. Similarly, Bauer et al. (1998) found that the nonparametric Data Envelopment Analysis (DEA) technique and the parametric techniques give only very weakly consistent rankings when compared with each other, and that the average rank-order correlation between the parametric and nonparametric methods was only 0.098.

In some studies, such as that by Weill (2001), based on European samples, no positive relation between any parametric approach and DEA is found. In a study based on UK building societies (Drake and Weyman-Jones, 1996), the Spearman rank correlation was even negative. In contrast, high and positive correlations were found by Resti (1997), based on a sample of Italian banks, Eisenbeis et al. (1999), based on bank holding company data, and Cummins and Zi (1998), based on US life insurance firm data. If we extend the scope of the analysis to include studies outside the field of financial institutions, we find more empirical evidence comparing the two types of techniques such as studies by Banker et al. (1986), De Borger and Kerstens (1996), Hjalmarsson et al. (1996), or Resti (2000). An excellent and updated comparison of techniques is provided by Badunenko et al. (2012).

[3] Apart from the surveys on financial institutions' efficiency referred to in the introduction, there are also monographs that provide careful descriptions of the available methods to measure efficiency in general. Some of them focus both on parametric and nonparametric techniques (Coelli et al., 1998; Fried et al., 2008; Bogetoft and Otto, 2011), whereas others confine the analysis either to the parametric (Lovell and Kumbhakar, 2000) or nonparametric (Färe and Grosskopf, 2004; Daraio and Simar, 2007) fields.

In the last few years, from a theoretical point of view parametric and nonparametric approaches have evolved at different paces. Up to the mid-nineties, when most of the studies cited in the preceding paragraph were published, the contributions in both fields were similar. However, in the last ten years the proposals in the nonparametric field have outnumbered those in parametric field. These proposals include the order-m (Cazals et al., 2002) and order-α (Aragon et al., 2005; Daouia and Simar, 2007) estimators, which are more robust to extreme values than either DEA or FDH (Free Disposable Hull). Although these methods are gaining wider acceptance, some critiques have also been put forward (Krüger, 2012). Some initiatives have been also developed in the parametric field such as those based on Bayesian statistics (Van den Broeck et al., 1994), but the number of proposals is been much lower—not only from a theoretical point of view but also in terms of applications.

Most of the nonparametric estimators cited in the previous paragraph are based on DEA and FDH. However, none of them have explicitly modeled how prices enter the analysis. Some of them also have problems in handling multiple outputs and multiple inputs, which also affects several of the Bayesian proposals. But in some contexts such as banking, the availability of prices, and the multiple-input/multiple-output nature of banking firms may suggest that previous nonparametric methods—such as DEA and FDH—could be more appropriate, at least until further progress is made in the aforementioned new fields of research. This constitutes promising field of theoretical research.

We therefore take the set of activity analysis techniques presented and revised in Färe and Grosskopf (2004) as our reference for measuring efficiency. Let $\boldsymbol{x} = (x_1, \ldots, x_N) \in \mathbb{R}^N_+$ be the input quantities, with associated input prices $\boldsymbol{\omega} = (\omega_1, \ldots, \omega_N) \in \mathbb{R}^N_+$, and $\boldsymbol{y} = (y_1, \ldots, y_M) \in \mathbb{R}^M_+$ be the output quantities, with associated output prices $\boldsymbol{p} = (p_1, \ldots, p_M) \in \mathbb{R}^M_+$. Accordingly, total costs and total revenues will be defined as $\boldsymbol{\omega}'\boldsymbol{x} = \sum_{n=1}^{N} \omega_n x_n$ and $\boldsymbol{p}'\boldsymbol{y} = \sum_{m=1}^{M} p_m y_m$, respectively. It is important to note that we are assuming that both input and output quantities are divisible and, more importantly, the costs and revenues they generate, respectively, are also divisible. This is a critical issue in banking, since sufficiently disaggregated information is not always available.

Technology is defined as

$$\mathcal{T} = \{(\boldsymbol{x}, \boldsymbol{y}) : \boldsymbol{x} \text{ can produce } \boldsymbol{y}\}, \tag{1}$$

and input requirement and output sets are defined as

$$\mathcal{L}(\boldsymbol{y}) = \{\boldsymbol{x} : (\boldsymbol{x}, \boldsymbol{y}) \in \mathcal{T}\}, \boldsymbol{y} \in \mathbb{R}^M_+, \tag{2}$$

and

$$\mathcal{P}(\boldsymbol{x}) = \{\boldsymbol{y} : (\boldsymbol{x}, \boldsymbol{y}) \in \mathcal{T}\},\ \boldsymbol{x} \in \mathbb{R}^N_+, \tag{3}$$

respectively.

If $\boldsymbol{x}^*_s$ and $\boldsymbol{y}^*_s$ are the optimal input and output vectors for firm s, $s = 1, \dots, S$, respectively, cost and revenue efficiency *coefficients* will be defined as $CE_s = \boldsymbol{\omega}'_s\boldsymbol{x}^*_s/\boldsymbol{\omega}'_s\boldsymbol{x}_s$ and $RE_s = \boldsymbol{p}'_s\boldsymbol{y}^*_s/\boldsymbol{p}'_s\boldsymbol{y}_s$. The coefficients will be bounded by unity from above and below for cost efficiency and revenue efficiency, respectively; in other words, in either case efficient firms will be those with efficiency scores equal to one—or 100, if results are expressed as percentages.

In the short run framework, these coefficients have to be adapted to consider the existence of fixed ($\boldsymbol{x}_{s,f}$) and variable ($\boldsymbol{x}_{s,v}$) inputs. As fixed inputs can not adjust, the short run cost efficiency coefficient becomes

$$CE_s = \frac{\boldsymbol{\omega}'_{s,v}\boldsymbol{x}^*_{s,v} + \boldsymbol{\omega}'_{s,f}\boldsymbol{x}_{s,f}}{\boldsymbol{\omega}'_{s,v}\boldsymbol{x}_{s,v} + \boldsymbol{\omega}'_{s,f}\boldsymbol{x}_{s,f}} \tag{4}$$

whereas, on the revenues' side, the corresponding efficiency coefficient would become:

$$RE_s = \frac{\boldsymbol{p}'_s\boldsymbol{y}^*_s}{\boldsymbol{p}'_s\boldsymbol{y}_s} \tag{5}$$

Optimal values are found by solving linear programming problems. For short run cost efficiency, considering variable cost minimization in which the input quantities are modified to reduce the variable costs (where X_v, X_f and Y are observed data) for each s firm is as follows:

$$
\begin{aligned}
\min_{\lambda, y^*} \quad & \boldsymbol{w}_s' \boldsymbol{x}_v^* \\
\text{s.t.} \quad & -\boldsymbol{y}_s + \mathbf{Y}\boldsymbol{\lambda} \geq \mathbf{0}, \\
& \boldsymbol{x}_v^* - \mathbf{X_v}\boldsymbol{\lambda} \geq \mathbf{0}, \\
& \boldsymbol{x}_{s,f} - \mathbf{X_f}\boldsymbol{\lambda} \geq \mathbf{0}, \\
& \mathbf{1}'\boldsymbol{\lambda} = \mathbf{1}, \\
& \boldsymbol{\lambda} \geq \mathbf{0}, \\
& \boldsymbol{\lambda} \in [\mathbf{0}, \mathbf{1}].
\end{aligned}
\tag{6}
$$

For the revenue efficiency coefficient, the program attempts to modify the output quantities in order to maximize the revenues (taking the output prices as given). On the inputs side, the restrictions are the same for both the fixed and the variable inputs:

$$
\begin{aligned}
\max_{\lambda, y^*} \quad & \boldsymbol{p}_s' \boldsymbol{y}^* \\
\text{s.t.} \quad & -\boldsymbol{y}^* + \mathbf{Y}\boldsymbol{\lambda} \geq \mathbf{0}, \\
& \boldsymbol{x}_{s,v} - \mathbf{X_v}\boldsymbol{\lambda} \geq \mathbf{0}, \\
& \boldsymbol{x}_{s,f} - \mathbf{X_f}\boldsymbol{\lambda} \geq \mathbf{0}, \\
& \mathbf{1}'\boldsymbol{\lambda} = \mathbf{1}, \\
& \boldsymbol{\lambda} \geq \mathbf{0}, \\
& \boldsymbol{\lambda} \in [\mathbf{0}, \mathbf{1}].
\end{aligned}
\tag{7}
$$

DEA has been used much more frequently than FDH. However, the technology defined by FDH is nonconvex, which implies that an assumption is being dropped (convexity), and it therefore has the advantage of being *a priori* more flexible (see Deprins et al., 1984). Furthermore, as indicated by Balaguer-Coll et al. (2007), FDH has several attractive statistical properties; for instance it is a consistent estimator for any monotone boundary, by imposing only strong disposability. Actually, the only assumption required for the validity of the FDH is the monotonicity of the technology. Moreover, some authors such as Park et al. (2000) have shown that imposing convexity might be problematic, since a convex model causes specification error when the true technology is nonconvex. In contrast, when the true technology is convex, the FDH estimator converges to the true estimator (see also Simar and Wilson, 2000; Briec et al., 2004). Finally, having into account that in our data set different banking organizations are included (commercial banks and savings banks) convexity could imply that strange convex combinations of these two organizations could have a significant impact on the reference frontier; one way to avoid this potential problem is to define a non-convex technology.Given these advantages, for solving the programming problems defined above we considered FDH, which is specified by setting the constraint $\boldsymbol{\lambda} \in [\mathbf{0}, \mathbf{1}]$.

3. Data and variables

Data were provided by Fitch-IBCA Bankscope database. Our sample is made up of Spanish banking firms for the 2005–2009 period. It includes commercial banks, savings banks, and credit unions. Most studies (see, for instance Bernad et al., 2008) usually exclude credit unions, arguing that they do not really compete with the other two groups of banks, and that their share of total assets is less than 10%. Although some others such as Carbó Valverde et al. (2007) do not include them because of the lack of information, in general the exclusion of these financial institutions is based on the grounds of size (they account for less thant 10% of total banking assets) and objectives (their main goal is usually to provide financial services to their members). However, given the importance of this type of institutions in some particular fields such as financial exclusion (Carbó et al., 2007), and the diminishing role of savings banks in this field (Alamá and Tortosa-Ausina, 2012), we included them in our sample. For a comprehensive description of the differences between the three types of banks see, for instance, Crespí et al. (2004).

In addition, we also consider that the period analyzed is relevant because it includes the years in which the financial and economic crises started to take effect in several countries and, therefore, since our sample considers the three types of banks, we can analyze how commercial banks, savings banks and credit unions have performed differently in these turbulent times.

Data come from each banking firms' balance sheets and profit and loss accounts, and they are expressed in thousands of US dollars and are inflation adjusted. After removing some unreliable data, excluding all non-consistent values (such as zero total assets or zero employees) we have a total of 763 observations for all sample years. Since the Bankscope database does not provide data on the number of employees, we completed this information from three additional sources: AEB ("Asociación Española de Banca") for commercial banks, CECA ("Confederación Española de Cajas de Ahorro") for savings banks and UNACC ("Unión Nacional de Cooperativas de Crédito"), for credit unions. Although many previous studies that also use Bankscope data such as, for instance, Altunbaş et al. (2001), do not consider the number of employees either, they encountered greater difficulties in considering alternative databases because they focused on banks from different countries.

Specifying inputs and, especially, outputs, is often a controversial issue in banking. On the input side, our choice is in line with most previous literature. We consider three inputs, namely, loanable funds, or financial capital (referred to here as vx_1, since it is a variable input), number of employees (variable input vx_2), and physical capital (which is the fixed input fx_1). See Table 1 for specific definitions and summary statistics. Each of these input categories generates costs, referred to as VC_1 (total interest expenses), VC_2 (personnel expenses) and FC_1 (other operating expenses). We can easily calculate prices for each input category ($vw_1 = VC_1/vx_1$, $vw_2 = VC_2/vx_2$ and $fw_1 = FC_1/fx_1$ for inputs loanable funds, labor and physical capital, respectively).

Modeling the output side entails some added difficulties. There are three basic approaches to define bank output, namely, the productions approach, the transactions approach and the intermediation approach Sturm and Williams (2008). These different approaches are one of the reasons why non-homogeneous efficiency scores might be obtained even if similar data are used (Berger and Humphrey, 1992). In this study we use the intermediation approach and, within this, the asset approach to define bank output where total loans and securities are outputs.[4] Total earning assets can be decomposed into loans (y_1, see Table 1), which represent traditional lending activity, and other earning assets (y_2), which refer to non-lending activities. Some recent contributions such as Casu and Girardone (2010), or Chortareas et al. (2011) have also considered these two outputs.

Our first output "loans" (y_1), reflects the traditional lending activities of the banking sector. This output includes all types of loans to customers (residential mortgage loans, other mortgage loans, other customer/retail loans, corporate and commercial loans and other loans), as well as loans and advances to banks. As loans to customers we consider "net loans". The

[4]The other two approaches to *define* bank output within the intermediation approach are the value added and the user cost approaches. Due to unavailability of data, most research studies have chosen either the value added or the asset approach. Yet as Colangelo and Inklaar (2012) indicate, statistical agencies more frequently consider the user cost approach. According to this approach, banks do not charge explicit fees for many of their services but rather bundle the payment for services with the interest rates charged on loans and paid for deposits. Some recent papers have considered this approach, including (apart from Colangelo and Inklaar, 2012), Basu et al. (2011) and Diewert et al. (2012). Despite their advantages, most of these proposals are based on information that is only available at the country level. Consequently, extending the definition these studies use to bank level data is difficult because the necessary information is not available at the firm level.

income generated by this first output is "interest income", which includes "interest income on loans" plus "other interest income". The output price, r_1, is the ratio of interest income (R_1) to the value of loans (y_1; see Table 1). Actually, having to construct output prices from output quantities and their associated revenues might be problematic. In our particular case, in order to deal with this problem we dropped those observations corresponding to "unreasonable" prices. Although this concept might be arbitrary, we decided to drop those observations whose prices could be regarded as outliers, considering as such the ones that can be found when plotting a box plot—i.e., values greater than $1.5 \times IQR$ or lower than $-1.5 \times IQR$..

In the second output "other operating income" (y_2) we include other non-interest operating income plus dividend income. Within total non-interest operating income we include net gains (losses) on trading and derivatives, net gains (losses) on other securities, net gains (losses) on assets at face value (FV), net insurance income, net fees and commissions, and other operating income (the sum of these six variables represents total non-interest operating income). The second output cannot be decomposed in terms of quantity and the price component because it is an income (revenue) itself; we therefore consider price for output 2 (r_2) the unity and, consequently, the revenues this output generates (R_2) to be the same as the value of the output ($R_2 = y_2$).

4. Results

4.1. Cost and revenue efficiencies: some trends

We report summary statistics (mean and standard deviation) for both cost and revenue efficiencies in Table 2. Results are reported for all three types of banking firms (commercial banks, savings banks and credit unions), as well as for both sub-periods considered (pre-crisis, 2005–2007, and crisis, 2008–2009).

Results show that, on average, commercial banks are the most efficient institutions. This result is robust both across type of efficiency measured (cost and revenue) as well as sub-period (pre-crisis and crisis years). In the case of cost efficiency commercial banks' efficiency averages to 98.44% during the pre-crisis years, implying that these firms' inefficiencies are quite low—recall that efficient banks are those whose efficiency is 100%. In contrast, during the same sub-period savings banks were the most inefficient firms, with average efficiencies of 92.84% (on average, these banks could have saved 7.16% of their costs). Credit unions lie in the middle, slightly closer to savings banks (their cost efficiency is, on average, 95.05%).

During the pre-crisis years commercial banks also show the best relative performance (101.34%). Recall that for this type of efficiency, values closer to 100% also indicate higher efficiency, although the scale is inverse (the most inefficient decision making units have efficiency scores much higher than one, and values close to 100% indicate lower inefficiency). In this case credit unions perform worse, on average, than savings banks (111.18% vs. 108.34%), which could be due to the fact that this type of bank has different objectives.

Underlying these average values we find remarkably differing dispersion indicators. Commercial banks are relatively homogeneous for both types of efficiency (their values are 5.66 and 5.78 for cost and revenue efficiency, respectively). In contrast, both savings banks and credit unions show notable disparities. In the case of savings banks, the standard deviation values are relatively similar for both types of efficiencies, whereas in the case of credit unions the dispersion for revenue efficiency is almost three times the value found for cost efficiency.

However, during the crisis years of our sample (2008 and 2009) most of the discrepancies disappeared and, on average, cost efficiencies are very similar for the three bank types. Some differences still persist in the case of revenue efficiency for credit unions (104.22%), which also show large discrepancies as measured by a high value for the standard deviation (12.11).

Although the information reported in Table 2 is meaningful, it is entirely confined to two summary statistics—mean and standard deviation. Figures 1 and 2 display box plots on cost and revenue efficiencies, respectively, for all types of firms and both sub-periods. Specifically, in the upper panel of Figure 1 we provide box plots for the cost efficiency of the three types of banks during the pre-crisis period, and the lower panel reports analogous information for the crisis period. Figure 2 is the revenue efficiency counterpart to Figure 1.

The inspection of the box plots reveals several patterns, two of which prevail. First, commercial banks are apparently much more efficient than both savings banks and credit unions, regardless of the type of efficiency (cost, revenue) or period considered (pre-crisis, crisis). Second, inefficient behavior decreased substantially during the crisis period, especially for savings banks and credit unions, regardless of the type of efficiency.

Therefore, although before the start of the crisis the magnitude of the inefficiencies was substantial, especially for savings banks and credit unions, inefficient banks made remarkable efforts to catch up with the benchmarks. This relative inefficiency of savings banks had already been found in previous contributions such as, for instance, Tortosa-Ausina (2002c)—although most previous studies did not focus on revenue efficiency, nor consider nonconvex approaches such as FDH. However, the initiatives to properly test for the significance of the differences between different types of banks were relatively scant. Comparisons extending the analysis to the case of credit unions are also very scarce.

4.2. Testing for the differences: models, contexts and types of banks

The results reported above are informative. However, although the analysis of the entire distributions provided by box plots (Figures 1 and 2) adds complexity to the analysis of means and standard deviations (Table 2), they are essentially descriptive.

In this section we go a step farther by examining whether the efficiency differences found are significant or not. Specifically, we focus on three sources of heterogeneity, namely, the type of efficiency considered (cost vs. revenue efficiency), the type of bank (commercial banks vs. savings banks vs. credit unions), or the temporal context (either pre-crisis or crisis years).

To do this we can consider a variety of instruments. Given the nonparametric nature of the techniques used to measure efficiency, which are possibly the "most" nonparametric of the nonparametric techniques (due to the relaxation of the convexity assumption), we deem it also appropriate to consider nonparametric techniques in this second part of the analysis.

Specifically, the Li (1996) test allows us to test whether two given distributions, say $f(\cdot)$ and $g(\dot{})$, estimated nonparametrically via kernel smoothing, differ statistically. Therefore, we can actually ascertain whether the differences observed for the box plots in Figures 1 and 2 are statistically significant or not—i.e. we would not test whether some summary statistics (mean, standard deviation) differ but whether the entire distributions of efficiencies differ.

Results are provided in Tables 3, 4 and 5. In each of these tables we consider a different type of variation. Specifically, in Table 3 we focus on the difference between the two **models** or type of efficiency considered—cost or revenue efficiency. In Table 4 we explicitly test whether the differences for the three types of banks are relevant, and in Table 5 we focus on the two relevant periods (pre-crisis and crisis).

Results in Table 3, accounting for the differences for the two types of efficiencies (cost and revenue efficiency) are not significant when considering the entire period of analysis, regardless of the type of firm. We only find significant differences at the 1% level for the pre-crisis period for both savings banks and credit unions—basically because during the crisis years most of these banks became efficient and, therefore, discrepancies can no longer be significant.

In contrast, the comparative analysis for the different bank types performed in Table 4 reveals that the significant differences across types of banks hold regardless of the type of efficiency or period. These differences, however, do not exist when comparing savings banks and credit unions—in this particular case the discrepancies are never significant. In contrast, commercial banks are more efficient than the other two bank types except for the crisis period, when differences completely disappear.

We also explicitly test for temporal differences, and the results are reported in Table 5. In this case, although a proper dynamic analysis such as that provided by the Malquist index is not performed, results indicate that the differences are statistically significant at the 1% level for both savings banks and credit unions. However, this result is not mirrored for commercial banks, which were already quite efficient before the crisis started.

5. Conclusions

Over the last thirty years the Spanish banking system has undergone remarkable changes, mostly brought about by deregulatory initiatives. Some of these began as far back as the early seventies, but deregulation intensified in the eighties, just before Spain joined the former European Economic Community and when the Single European Market was established. Most of these deregulatory initiatives ultimately aimed to allow Spanish banking institutions (namely, commercial banks, savings banks, and credit unions) to cope with the threat of potential entry from their European peers.

In that scenario, a relatively high number of research studies analyzed aspects related to the efficiency and productivity of Spanish banking firms. Although most studies were not directly comparable, because of the different periods, techniques or banking firms selected, some stylized facts emerged such as the productivity gains experienced by most Spanish financial institutions, or the higher cost efficiency of commercial banks with respect to savings banks.

However, most of these studies focused either on cost or (input) technical efficiency, with fewer contributions dealing with profit or revenue efficiency. Yet both the cost <u>and</u> revenue sides are relevant for determining profit efficiency, and the variety of scenarios might be multiple, as shown by Färe and Primont (1995). For instance, financial institutions that are cost efficient might not necessarily be revenue efficient, and vice versa, and the case could arise that financial institutions which are both cost *and* revenue efficient are not profit efficient.

The relevance of revenue efficiency might have become even more important since the late 1990s and the beginning of the 2000s, when the booming Spanish economy was accompanied by a general expansion of Spanish financial institutions (especially savings banks), whose strategies were more tightly focused on maximizing revenues rather than minimizing costs. The current economic and financial crisis is redefining these strategies, and the focus might be changing again for the different financial institutions. In the particular case of savings banks, most of them had set aggressive but costly geographic expansion policies that are now being redefined (Illueca et al., 2009, 2014).

In this scenario, we have extended the analysis of efficiency to consider not only the cost side but also the revenues of Spanish commercial banks, savings banks and credit unions during both the pre-crisis years (from 2005 to 2007) and crisis years (2008 and 2009). Results indicate that, on average, commercial banks were more efficient than both savings banks or credit unions. This was especially apparent during the pre-crisis years, regardless of the type of efficiency considered—whether cost or revenue efficiency. However, during the crisis years, the differences between commercial banks and the other two types of financial institution shrank dramatically, especially in the case of cost efficiency. These results were, in general, robust to the type of efficiency considered and, for all sources of heterogeneity considered (cost vs. revenue efficiency, commercial banks vs. savings banks vs. credit unions, pre-crisis vs. crisis years) the differences were statistically significant.

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Table 1: Definitions of inputs, outputs and prices

Revenues and costs		Outputs and inputs		Output and input prices	
Revenues	Definition	Output	Definition	Output prices (r)	Definition
R_1	Interest income (interest income on loans+ other interest income)	y_1	Customer loans	r_1	price corresponding to output 1
R_2	Other operating income	y_2	Other operating income	r_2	price corresponding to output 2
Operating costs		Input		Input prices (ω)	Definition
VC_1	Total interest expenses	vx_1	Loanable funds (=Financial capital)	vw_1	price corresponding to variable input 2
VC_2	Personnel expenses	vx_2	Number of employees	vw_2	price corresponding to variable input 1
FC_1	Other operating expenses	fx_1	Fixed assets (=Physical capital)	fw_1	price corresponding to fixed input 1

Table 2: Cost, revenue and profit efficiency, descriptive statistics for the different bank types (pre-crisis and crisis years)

Type of bank	Type of efficiency	Pre-crisis (2005–2007)		Crisis (2008–2009)	
		Mean	Std.dev.	Mean	Std.dev.
Commercial banks	Cost efficiency	98.4388	5.6636	98.8704	4.5051
	Revenue efficiency	101.3407	5.775	101.3269	5.5294
Savings banks	Cost efficiency	92.8358	11.0777	98.3298	4.8618
	Revenue efficiency	108.3407	13.7447	102.2747	6.6915
Credit unions	Cost efficiency	95.0466	7.2895	98.1244	5.3424
	Revenue efficiency	111.1804	19.9204	104.2216	12.1083
All banks	Cost efficiency	95.2593	8.6746	98.3193	5.0521
	Revenue efficiency	107.4329	15.4497	103.1369	9.8628

Table 3: Distribution hypothesis tests (Li, 1996), model

			All years	Pre-crisis	Crisis
Cost vs. revenue efficiency	f(CE, all banks) $=$ g(RE, all banks)	T-statistic	0.1596	1.9060	1.5674
		p-value	0.4366	0.0283	0.0585
	f(CE, commercial banks) $=$ g(RE, commercial banks)	T-statistic	0.0825	0.0950	0.0279
		p-value	0.4671	0.4622	0.4889
	f(CE, savings banks) $=$ g(RE, savings banks)	T-statistic	0.8978	2.4297	0.5259
		p-value	0.1846	0.0076	0.2995
	f(CE, credit unions) $=$ g(RE, credit unions)	T-statistic	0.6968	4.3610	1.1520
		p-value	0.2430	0.0000	0.1247

Notes: the functions $f(\cdot)$ and $g(\cdot)$ are (kernel) distribution functions for each model being compared.

Table 4: Distribution hypothesis tests (Li, 1996), type of bank

			All years	Pre-crisis	Crisis
Cost efficiency	f(CE, commercial banks) =	T-statistic	5.1994	6.8999	0.0678
	g(CE, savings banks)	p-value	0.0000	0.0000	0.4730
	f(CE, commercial banks) =	T-statistic	3.2977	8.5318	–0.3036
	g(CE, credit unions)	p-value	0.0005	0.0000	0.6193
	f(CE, savings banks) =	T-statistic	–0.0828	–0.1797	–0.3289
	g(CE, credit unions)	p-value	0.5330	0.5713	0.6289
Revenue efficiency	f(RE, commercial banks) =	T-statistic	6.4959	7.3144	0.5462
	g(RE, savings banks)	p-value	0.0000	0.0000	0.2924
	f(RE, commercial banks) =	T-statistic	6.6964	8.3006	0.5705
	g(RE, credit unions)	p-value	0.0000	0.0000	0.2842
	f(RE, savings banks) =	T-statistic	–0.4192	0.0945	–0.4256
	g(RE, credit unions)	p-value	0.6625	0.4624	0.6648

Notes: the functions $f(\cdot)$ and $g(\cdot)$ are (kernel) distribution functions for each model being compared.

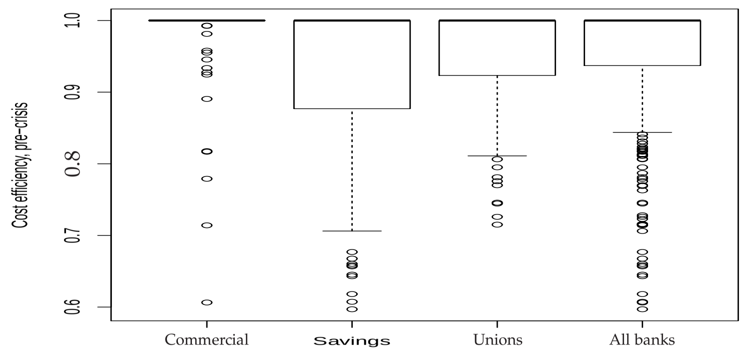
Table 5: Distribution hypothesis tests (Li, 1996), context

			Cost efficiency	Revenue efficiency
Pre-crisis vs. crisis years	f(Pre-crisis, all banks) $=$ g(Crisis, all banks)	T-statistic	8.9881	3.5159
		p-value	0.0000	0.0002
	f(Pre-crisis, commercial banks) $=$ g(Crisis, commercial banks)	T-statistic	–0.2810	–0.3327
		p-value	0.6106	0.6303
	f(Pre-crisis, savings banks) $=$ g(Crisis, savings banks)	T-statistic	4.5713	2.5002
		p-value	0.0000	0.0062
	f(Pre-crisis, credit unions) $=$ g(Crisis, credit unions)	T-statistic	9.1343	4.7412
		p-value	0.0000	0.0000

Notes: the functions $f(\cdot)$ and $g(\cdot)$ are (kernel) distribution functions for each model being compared.

Figure 1: Box plots of cost efficiencies, pre-crisis and crisis years

(a) Cost efficiency, pre-crisis years



(b) Cost efficiency, crisis years

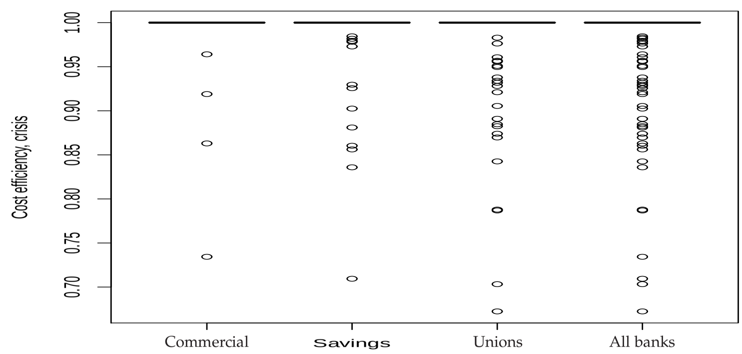
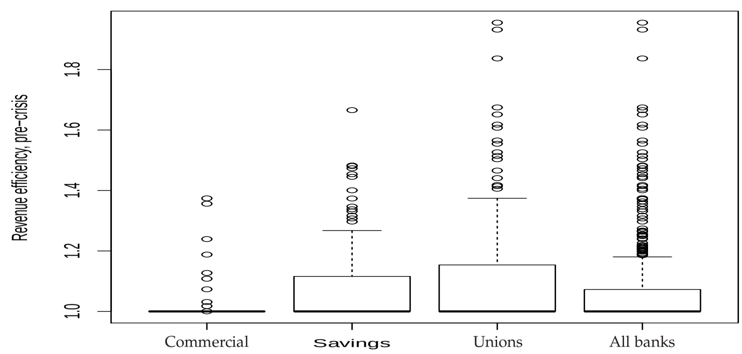


Figure 2: Box plots of revenue efficiencies, pre-crisis and crisis years

(a) Revenue efficiency, pre-crisis years



(b) Revenue efficiency, crisis years