A distributional comparison of cost and revenue efficiency for Spanish financial institutions*

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Abstract

Over the last twenty years the literature analyzing the efficiency of financial institutions has evolved rapidly. Most studies have focused on the input side, analyzing either cost, input technical efficiency or input allocative efficiency, whereas those focusing on the output side have been comparatively minor. This article explores explicitly how severe it may be to confine the analysis to one side of banks' activities only, using kernel smoothing methods which compare the efficiencies yielded by either minimizing costs or maximizing revenues. The application to the Spanish banking sector indicates not only how severe this issue actually is but also that its relevance has been increasing since the beginning of the financial crisis.

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1. Introduction

According to the survey by Berger and Humphrey (1997), most studies analyzing the efficiency of financial institutions have 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 stated by Berger *et al.* (1993), these efficiencies may be much more relevant than expected. Indeed, except for the study by Miller and Noulas (1996), profit inefficiencies have been generally found to be larger than those attributable to failing to minimizing costs. This gap in the literature has been further corroborated in the recent update by Fethi and Pasiouras (2009), who surveyed studies employing operational research (O.R.) and artificial intelligence (A.I.) techniques to assess bank performance by Fethi and Pasiouras (2009), and results were quite similar in terms of few 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 view of bank performance and, probably, a misleading view as well. Second, in some circumstances, or for some type of firms, the relevance of revenue maximization might be minor. It could be the case for a number of Western European banking firms. However, after the strong deregulation and liberalization process undergone by Western European banking industries, firms now are largely subject to the same regulations and share similar objectives.

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 establishment of an inadequate price policy. Some studies such as Berger and Mester (1997) that estimate both profit and cost inefficiency have concluded that the first type of inefficiency is always lower (see also Maudos and Pastor, 2001, who focus in an international sample). In addition, as suggested by Berger and Mester (1997), and contrary to what one might *a priori* expect, profit (and/or revenue) efficiency and cost efficiency are not always positively correlated, and the case could occur that they are even *negatively* correlated. In such circumstances, the most cost inefficient banks could offset this apparent inefficiency using different paths such as raising higher revenues than their competitors due to their output mix, or exploiting stronger market power when setting prices.[1]

Thereby cost inefficiency might also include some costs that should be attached to the product mix of banks. Accordingly, one should consider the possibility that some specializations are more costly than others, which does not necessarily entail they being more inefficient. Estimating profit or revenue efficiency may capture this specialization effect. Thereby higher revenues could offset the higher costs of firms emphasizing more expensive product lines.

This article attempts to measure both sides of inefficiency, i.e., cost and revenue and compare results using a broader view which encompasses the entire distributions of efficiency scores, instead of confining the conclusions to correlation coefficients only. Only few studies such as those by Färe *et al.* (2004), Devaney and Weber (2002) and Maudos and Pastor (2003) have used linear programming techniques such as Data Envelopment Analysis (DEA) (Färe and Grosskopf, 2004, see) to measure profit efficiency. If the analysis were confined to revenue efficiency, the existing literature on applications to the banking sector is virtually nonexistent.[2] Our analysis differs from previous work also in terms of how the results by each type of efficiency (cost, revenue) are compared. Specifically, we will focus on the *entire* distribution of efficiency scores, rather than only summary statistics like correlation coefficients.

Our analysis is focused on the Spanish banking system, which offers a scenario where profound changes have taken place: important deregulations 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 meet European Union legislation—, removal of the restrictions on the geographical expansion of savings banks, implementation of new telecommunications technologies, etc. In this reshaped industry, in which there is a broad consensus that competition is tougher, analyzing bank efficiency gains momentum, partly because of the alleged inverse relationship between competition and inefficiency or, more exactly, X-inefficiency.[3] Accordingly, a considerable empirical effort has been devoted to analyze the competitive viability of Spanish banking firms, with varying results. However, most of these research studies have focused overwhelmingly on cost aspects, or even on a particular component of cost efficiency (technical efficiency). Yet no attempt has been made to compare cost efficiency and revenue efficiency.

[1] Berger and Mester (1997) label the situation in which market power exists in fixing output prices alternative profit efficiency. On the other hand, if output prices are given they use the concept of standard profit efficiency.

[2] However, the number of studies analyzing bank profit efficiency using econometric techniques such as Stochastic Frontier Analysis (SFA) (Lovell and Kumbhakar, 2000) is substantial. See Färe *et al.* (2004) for a review.

[3] See Leibenstein (1966, 1978a,b). Recently, Stennek (2000) has casted some doubt on the validity of X-inefficiency as a survival condition in a competitive environment.

Moreover, the third phase of the European Union adds to the interest of efficiency analysis. In order to achieve a full economic and monetary integration, the higher competitive pressures—and the reduction of market power—will impel financial institutions to make an extra effort to enhance efficiency, not only on the cost side, but also on the revenue side. Profitability decline due to both tougher competition and reduced interest margins is the primary catalyst for the pursuit of efficiency enhancement, in order to gain competitiveness.

The study proceeds as follows. The next section surveys the literature of the relationship between efficiency and competition. Section 2 presents the methodology used to measure market power and efficiency, emphasizing the relevance of focusing on both cost and revenue efficiency, introducing both the method and results, along with the illustration of the relationship between 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 concludes.

2. Methodology

2.1. Measuring efficiency

Most of the literature related to the measurement of economic efficiency has based its analysis either on parametric or nonparametric frontier methods. As indicated in the survey paper by Murillo-Zamorano (2004), 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 performance 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 suggested by Berger and Humphrey (1997) 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 become "sinners" when imposing 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 become "sinners" because of a lack of allowance for random error (due to either luck, measurement errors, etc).[4]

Some papers have analyzed financial institutions' efficiency using both parametric and nonparametric methods. In some, correlations between both approaches are extremely low, and negative. In others, the opposite result is achieved. Chronologically, we find the study by Ferrier and Lovell (1990), who 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. Actually, in a study based on U.K. building societies (Drake and Weyman-Jones, 1996), the negative correlation is even higher, with a Spearman rank correlation value calculated at -0.9715. On the other hand, 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 U.S. life insurance firm data. If we extend the scope of the analysis to include studies not focused on financial institutions, we find more empirical evidence comparing both types of techniques such as the study by Banker *et al.* (1986), De Borger and Kerstens (1996), Hjalmarsson *et al.* (1996) or, more recently, Resti (2000).

In the last few years, from a theoretical point of view both 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 of the parametric field. These proposals would include the order-m (Cazals *et al.*, 2002) and order-α (Daouia and Simar, 2007) estimators, which are more robust to extreme values than either DEA (Data Envelopment Analysis) or FDH (Free Disposable Hull). Aragon *et al.* (2005) present a nonparametric estimator of the efficient frontier based on conditional quantiles of an appropriate distribution associated with the production process. Martins-Filho and Yao (2007) also propose a nonparametric model of frontiers which envelops the data and is also more robust to

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

extreme values than previous methods.[5] Although some initiatives have been also developed in the parametric field such as those based on Bayesian statistics (Van den Broeck *et al.*, 1994), the number of proposals has 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 have also some problems in handling multiple outputs and multiple inputs, which also affects to several of the Bayesian proposals. But in some contexts such as banking, the availability of prices, and the multiple-input/multiple-output nature of the banking firms may point out that previous nonparametric methods—such as DEA and FDH—may be more appropriate, at least until further progress is made in the aforementioned new fields of research. This constitutes a promising field of research from a theoretical point of view.

Therefore, the set of activity analysis techniques presented in Färe *et al.* (1985), revised in Färe and Grosskopf (2004), is our reference for measuring efficiency. Let $\boldsymbol{x} = (x_1, \ldots, x_N) \in \mathbb{R}^N_+$ be the input quantities, with associated 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 prices $\boldsymbol{p} = (p_1, \ldots, p_M) \in \mathbb{R}^M_+$. Total costs and total revenues are defined as $\boldsymbol{\omega x} = \sum_{n=1}^N \omega_n x_n$ and $\boldsymbol{py} = \sum_{m=1}^M p_m y_m$, respectively. We assume both input and output quantities are divisible and, more importantly, both the costs and revenues they generate, respectively, are divisible as well. This is a critical issue in banking, since information disaggregated enough 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

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

[5]Some recent initiatives have also focused on the econometrics area; however, as suggested by Dorfman and Koop (2005), "the distinction between advances in econometric methods and advances in efficiency measurement is not a clear one".

respectively.

Since $\boldsymbol{x}_s^*$ and $\boldsymbol{y}_s^*$ are the optimal input and output vectors for bank s, $s = 1, \ldots, S$, respectively, cost and revenue efficiency *indexes* are defined as $CE_s = \boldsymbol{\omega}_s' \boldsymbol{x}_s^* / \boldsymbol{\omega}_s' \boldsymbol{x}_s$ and $RE_s = \boldsymbol{p}_s' \boldsymbol{y}_s / \boldsymbol{p}_s' \boldsymbol{y}_s^*$, respectively. The scores are bounded by unity from above and below for cost efficiency and revenue efficiency, respectively, namely, in either case efficient firms will be those with efficiency scores equal to one—or 100, if results were expressed as percentages. However, to facilitate comparison of results, having them in the same scale, we invert revenue efficiency scores.

The optimal values referred to in the preceding paragraph are obtained by solving linear programming problems. For cost efficiency, the linear programming problem (where $\mathbf{X}$ and $\mathbf{Y}$ are observed data) for each s bank is as follows:

$$\begin{aligned} \min_{\boldsymbol{\lambda}, \boldsymbol{x}_s^*} \quad & \boldsymbol{\omega}_s' \boldsymbol{x}_s^* \\ \text{s.t.} \quad & -\boldsymbol{y}_s + \mathbf{Y}\boldsymbol{\lambda} \geq \mathbf{0}, \\ & \boldsymbol{x}_s^* - \mathbf{X}\boldsymbol{\lambda} \geq \mathbf{0}, \\ & \mathbf{1}\boldsymbol{\lambda} = \mathbf{1}, \\ & \boldsymbol{\lambda} \geq \mathbf{0}. \end{aligned} \tag{4}$$

whereas maximal revenues will be obtained by solving the following linear programming problem:

$$\begin{aligned} \max_{\boldsymbol{\lambda}, \boldsymbol{y}_s^*} \quad & \boldsymbol{p}_s' \boldsymbol{y}_s^* \\ \text{s.t.} \quad & -\boldsymbol{y}_s^* + \mathbf{Y}\boldsymbol{\lambda} \geq \mathbf{0}, \\ & \boldsymbol{x}_s - \mathbf{X}\boldsymbol{\lambda} \geq \mathbf{0}, \\ & \mathbf{1}\boldsymbol{\lambda} = \mathbf{1}, \\ & \boldsymbol{\lambda} \geq \mathbf{0}. \end{aligned} \tag{5}$$

2.2. Comparing efficiencies using kernel methods

Those few applications which compare the results obtained for cost and revenue (or profit) efficiency usually confine their analysis to correlation coefficients only. We argue, similarly to Tortosa-Ausina (2002a, 2003), that a simple summary statistic conceals as much information as it reveals. Thereby in order to evaluate appropriately the gap between each firm's cost and revenue efficiency, it may be more relevant to perform an analysis that yields information that goes beyond a summary statistic.

The first obvious way to compare distributions is to examine them visually—i.e., their shape. There are multiple ways to do this, from a basic histogram to a boxplot or a density function estimated via nonparametric methods—which is basically a smoothed histogram. We combine these methods using an instrument which is a mix of a boxplot and a density function estimated via kernel smoothing, namely, the violin plots (Hintze and Nelson, 1998).

As suggested by Wand and Jones (1995), although scatterplots are the most widely used means of graphically displaying bivariate data sets, they are not free from disadvantages[6] from which kernel density estimates are exempt. However, although univariate kernel density estimation has received considerable attention in the literature, the same does not hold for the bivariate case, which may be partly explained by the difficulties in viewing high dimensional density functions.

The bivariate case constitutes a junction between the univariate and higher-dimensional multivariate cases. Some old difficulties estimating bivariate density functions deal with bandwidth choice, although there have been some important improvements recently.

For a bivariate sample $\mathbf{X}_1, \ldots, \mathbf{X}_n$, the kernel density estimate is defined by:

$$\widehat{f}(\boldsymbol{x}; \mathbf{H}) = n^{-1} \sum_{i=1}^{n} K_{\mathbf{H}}(\boldsymbol{x} - \mathbf{X}_i) \tag{6}$$

where $\boldsymbol{x} = (x_1, x_2)^\top$, $\mathbf{X}_i = (X_{s1}, X_{s2})^\top$, $s = 1, \ldots, S$. In our case, $\boldsymbol{x} = (x_1, x_2)^\top = (CE, RE)^\top$, $\mathbf{X}_s = (CE_s, RE_s)^\top$, where CE and RE stand for cost and revenue efficiency, respectively.[7] K is a bivariate kernel function satisfying $\int K(\boldsymbol{x}) d\boldsymbol{x} = 1$ and $\mathbf{H}$ is a symmetric positive definite 2×2 matrix called bandwidth matrix.

The first decision in kernel density estimation regards the choice of kernel. Our computations are based on one of the most popular choices, i.e., the standard bivariate normal density:

$$K(\boldsymbol{x}) = (2\pi)^{-1} \exp\big(-\frac{1}{2} \boldsymbol{x}^\top \boldsymbol{x}\big) \tag{7}$$

However, the relevance of the kernel's choice is overshadowed by the choice of bandwidth matrix. In this case, the innovations' pace has just resumed. Previous work (Wand and Jones, 1994) demonstrated that it was impossible to derive an explicit expression for the plug-in estimator—one of the most up-to-date ones—of $\mathbf{H}$ for general multivariate kernel density

[6]For instance, "the eye is drawn to the peripheries of the data cloud, while structure in the main body of the data will tend to be obscured by the high density points".

[7]In order not to strain too much the limits of space, comparisons were confined to cost and revenue efficiency only.

estimators and, consequently, efforts were reallocated towards searching on diagonal bandwidth matrices for bivariate density estimation. However, Duong and Hazelton (2003) have developed further this stem of research by focusing on plug-in methods for selecting a full bandwidth matrix for bivariate kernel density estimation, which can give markedly better performance for some types of densities—and it turns out to be our case. All details on the selection procedure are discussed in Duong and Hazelton (2003).

3. Data, inputs, and outputs

Data are provided by the Spanish Confederation of Savings Banks (Confederación Española de Cajas de Ahorro, CECA) and the Spanish Association of Commercial Banks (Asociación Española de Banca, AEB) for years 1992 through 2003. This is the only public information available for Spanish commercial and savings banks at the individual firm level. Although the Bank of Spain provides some further disaggregated information for different balance sheet categories, it is available only for aggregated data—i.e., commercial banks and/or savings banks considered altogether. Data come from each firm's balance sheet and profit and loss account. The overwhelming majority of firms making up the industry are considered in the study. Only those banks for which either missing or unreliable information (zero employees, etc.) were excluded from the study.

Specifying inputs and, especially, outputs, is often a controversial issue in banking. On the input side, our choice is standard and stands with most previous literature. We consider three inputs, namely, labor (x_1), capital (x_2) and purchased funds (x_3). See Table 1 for specific definitions and summary statistics for year 2003. We can calculate prices for each input category since information on the costs they generate is also available—i.e., labor expenses, amortizations and other noninterest expenses, and financial costs, respectively. Modeling the output side entails some added difficulties. There exist three basic approaches to *define* bank output, namely, the asset, user cost, and value-added approach (Berger and Humphrey, 1992). Most studies fall under the first category, basically due to data limitations. Many others have considered an "enlarged" version of the asset approach, considering not only that asset categories yielding revenues are to be considered outputs, but also that transaction deposits are also an output, since they may be considered a proxy for the provision of payment and safekeeping services provided by each bank. However, there is no available disaggregation for deposits, which severely restrains our choice.

Taking into account the rationale presented above, we consider banks to provide four outputs: loans (y_1), fixed-income securities (y_2), other securities (y_3), and nontraditional output (y_4). Specific descriptions for each of them, along with descriptive statistics, are provided in Table 1. Our choice is also conditional on the available information on the revenues attributable to each output category. Following Rogers (1998), we have also considered a further category, namely, nontraditional output, based on Rogers' findings which pointed out that disregarding the new activities in which most banks engage (basically activities that provide financial services and generate fee income) leads to biased efficiency estimates for both cost, revenue, and profit efficiency.[8]

4. Results

4.1. Results on efficiency

Results are displayed in Figure 1 for cost, revenue, technical and allocative efficiency. Mean cost efficiency has been declining from 0.843 in 1992 to 0.698 by 1999 for all banking firms, reviving to reach 0.760 by 2003. Commercial banks were the best performers; they departed from 0.912, bottomed at 0.749 by 1999, but ended up with efficiency levels as of 1992. A similar pattern is found for savings banks, yet their efficiency is substantially lower. Savings banks also bottomed earlier, declining from 0.774 to 0.625 in 1998, reaching 0.683 by the end of the sample period. Weighted values are higher in all instances, yet the inflection by the end of the nineties is mirrored. In this case, the inflection occurs earlier, suggesting that large firms could be leading in an industry characterized by rapid change.

Results differ substantially on the revenue side. Although optimal revenues were measured so as to provide revenue efficiency scores bounded from below, results have been inverted (divided by 1) so as to ease comparison with cost efficiency. An inflection point is found again, yet it occurs later, between years 2001 and 2002. Therefore, the declining cost efficiency was partly offset by the revenue side, since the decline for the latter occurred slightly later. There is a seamless link between our results and previous findings for the Spanish banking sector. The reversal in the increasing cost efficiency found in Tortosa-Ausina (2002b) by the middle nineties is mirrored here, and the declining trend is found to continue.

Therefore, despite the intense regulatory initiatives, inefficiency not only persists but also increases over time. In addition, although all banking firms face the same regulation, and

[8] See also the relevant discussion on the "decline" of traditional banking (Edwards and Mishkin, 1995).

they can perform the same operations,[9] cost efficiency differences, on average, are not fading away. However, savings banks regain ground on the revenue side, ending up better off than commercial banks. Thus one might tentatively conclude that some firms are focussing on more expensive ranges of products and services, probably innovating more financially and, therefore, evaluating their performance considering only the cost side provides just a partial, biased view.

The decomposition of cost and revenue efficiency into their technical and allocative components is quite revealing, since the sources of inefficiency are identified. Technical efficiency, both on the input and output sides (see Figure 1) is quite impressive, reaching *mean* values close to 100% in some cases. Firms' performances are much closer than in the cost and revenues cases, as revealed by much lower standard deviations. Allocative efficiency, on the other hand, presents more instability, since it does not differ a great deal from technical efficiency at the beginning of the sample period, yet ends up being, on average, much lower. Therefore, when prices do not enter the analysis one faces an industry where most firms are close to the efficient frontier. However, when they are included, discrepancies are remarkable, driving efficiency downwards.

Although we could provide a variety of summary statistics to achieve better insights on the peculiar distributions of efficiencies, its informativeness is overshadowed by what more comprehensive, graphical based, indicators such as boxplots reveal. Boxplots are displayed in Figure 2 for all types of efficiency studied. In each of the subfigures the vertical axis represents the variable's scale—which, in the case of efficiency scores, is bounded between 0 and 1. The box represents the interquartile range (IQR), containing the 50% midrange values of efficiency. A small interquartile range is shown by a relatively short box, indicating a tighter concentration of the efficiencies' mid-values. The horizontal line inside the box is the median. The location of this line relative to the top and bottom of the box conveys graphical information on the symmetry of the distribution; if the median centrally located, the distribution is asymmetrical. The whiskers, also called adjacent values, define the natural bounds of the distributions (the

[9]The Spanish banking system is made up of private commercial banks, savings banks, and credit co-operatives. For regulatory reasons, they have traditionally specialized in different lines of business. Today, they face exactly the same operational regulation, which allows them to undertake the same activities. The only regulatory differences they face arise from their ownership type, as commercial banks are privately owned, savings banks are foundations, and credit co-operatives are mutually owned. This difference is subtle, as savings banks are allowed to acquire commercial banks, but the opposite does not hold, as the former are a mix of privately- and publicly-owned companies. In contrast, due to this ownership type, savings banks have substantial difficulties in gaining equity. In fact, 50% of their profits has to be dedicated to increasing reserves. However, the three types of firms are still influenced by their historical specializations, although over the last few years firms' product mixes have varied greatly. See Crespí *et al.* (2004) for deeper insights on the peculiar ownership type of Spanish savings banks.

mean$\pm 1.5 IQR$), while the crosses represent outliers which lie outside the natural bounds. The whiskers define the expected range of observations, indicating also how far outliers are from the natural limits of the distribution.

Considering the banking industry as a whole, Figure 2(a) indicates that discrepancies are important on the cost side, and they increase over time. The increasing tendency is paralleled in the revenue side. However, as revealed by the shape of the boxes, as well as the position of the whiskers and the outliers, there exists a great variety of firm behavior. These trends are not entirely coincidental when analyzing the trends for each type of firm—Figure 2(b) and Figure 2(c). Differences among commercial banks increase rapidly, especially on the revenue side; on the other hand, savings banks' behavior is much more homogeneous, although differences seem also to be growing.

What has not been examined elsewhere are the precise links between cost and revenue efficiency. As suggested in the Introduction, recent changes in the Spanish banking industry have reshaped many firms' strategies, especially those of savings banks, which can now choose less regulation-conditioned product mixes. Therefore, firms leaning toward more cost-intensive products and services could be very cost inefficient yet, on the other side, be revenue efficient. These ideas have been exploited by Berger and Mester (1997), Dietsch and Weill (2000) or, in an application to the Spanish banking system, Maudos and Pastor (2003), and comparisons are usually based on correlation coefficients. In our specific setting, correlation coefficients between cost and revenue efficiency generally support the view of increasing differences over time—see Table 2. We argue here that these statistics carry meaningful information, yet not as much as, for instance, bivariate density functions.

These are estimated by means of kernel smoothing. Details are provided in Section 2.2 and elsewhere (see, for instance, Silverman, 1986). Results are shown in figures 3, 4 and 5 for all banking firms, commercial banks, and savings banks, respectively. We confine the analysis to both cost and revenue efficiency, so as not to strain the very limits of space. The upper panels in each figure contain perspective plots, whereas the lower panels display contour plots. In each figure probability mass shows how firms' relative positions vary according to whether we consider cost or revenue efficiency. Thus, if probability mass were totally located along the 45-degree line, cost and revenue efficiency would be the same for each and every firm—their relative positions do not vary, and the revenue analysis would not add anything new. On the other hand, if it were distributed along a hypothetical negatively-sloped diagonal (135-degree), cost and revenue efficiency would be at stark contrast for most firms. Hence, for those firms at the upper-left end of each contour plot, revenue efficiency would be much higher than cost efficiency, whereas for those firms at the lower-right end of each figure, the opposite would hold.

Results can be explored from multiple angles. Neither of the extreme views holds—i.e., although each firm's cost and revenue efficiency scores are not entirely coincidental, they do not move entirely in opposite directions. However, the probability mass abandoning the 45-degree line following a clockwise twist suggests that the most cost inefficient firms offset their poor behavior via revenue efficiencies above average. This is observed, with some exceptions, regardless of the type of firm considered (commercial banks, savings banks), and the time span (1992–1995, 1996–1999, or 2000–2003). Regarding the selection of periods, we have taken into account those years in which the effects of deregulation were still apparent (1992–1995), e.g., many savings banks were deeply involved in mergers, and those others renowned by the surge in economic activity (1996–1999, and 2000–2003).

A deeper scrutiny of results suggests that, should we take the banking industry as a whole, a tendency for revenue efficiency to beat cost efficiency is observed, since the probability mass shifts clockwise. This trend is common for all three subperiods (1992–1995, 1996–1999, and 2000–2003). However, over time, the probability is increasingly spreading out, coinciding with the epoch in which firms have been more profitable (1996–2003). We also observe that cost inefficiency increases, but the trend is not mirrored on the revenue side. Therefore, it seems that the higher revenues might have contributed more to increased profitability than lowering costs, since cost and revenue efficiency have moved in opposite directions. Yet the different type of firms have not behaved the same, since commercial banks' pattern (Figure 4) follows an abrupt evolution, whereas savings banks' (Figure 5) is milder.

Therefore, the results obtained so far provide a deeper understanding of the relationship between the different types of efficiencies. Although the analysis has been fairly confined to the comparison of cost and revenue efficiency, the same could be done for their technical and allocative components, or even to compare cost efficiency with technical efficiency and so forth. An analysis as such enriches our conclusions on the precise links between the different concepts being measured. Therefore, we can respond more properly to the question as to whether financial institutions are equally cost and revenue efficiency—or, as considered in other studies, profit efficiency.

5. Concluding remarks

This article has analyzed cost and revenue efficiency for Spanish financial institutions, with an explicit focus on the links between both indicators, its components (technical and allocative), taking also into account how the links can change for the different institutions operating in the industry. The analysis has been performed using an approach that goes beyond the usual summary statistics employed when performing this sort of comparisons, namely, correlation coefficients.

The first part of the study is entirely devoted to efficiency measurement, for which we employ activity analysis techniques. Specifically, we used Data Envelopment Analysis to measure both cost and revenue efficiency. This is important since the revenue side has been largely overlooked by many bank efficiency studies, especially those using nonparametric techniques. However, it has been proved to be as relevant as the cost side as a source of inefficiencies.

Our results suggest it is indeed important to consider both sides of inefficiency. Not only its magnitude is found to be substantial for both sides of the analysis—cost and revenue efficiency. In addition, it is found that, despite the fact that both commercial banks, savings banks and credit cooperatives do not show remarkable discrepancies when attempting to maximize revenues, the same does not hold when assessing their efforts to minimize costs—for which savings banks are found to face greater difficulties.

Factoring in the time variable is also appropriate since, over time, dissimilarities between cost and revenue increase, especially for commercial banks. However, results are complex and difficult to summarize, since for all the types of firm under analysis, the efficiency studied, and the period considered play a non-negligible role.

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Table 1: Definition of the relevant variables, 2003

Variable	Variable name	Definition	Mean	Std. dev.
Outputs				
y_1	Loans‡	All forms of loans	10,218,555.16	21,432,079.11
y_2	Fixed-income securities‡	Fixed-income securities	2,090,161.71	6,650,321.65
y_3	Other securities‡	Other securities and participating interests	802,539.46	3,210,842.41
y_4	Nontraditional output	Noninterest income (net)	87,626.85	215,877.86
Output prices				
p_1	Loan rates	Loan revenues/y_1	0.041	0.010
p_2	Fixed-income securities' rates	Revenues from fixed-income securities/y_2	0.080	0.214
p_3	Other securities' rates	Revenues from other securities/y_3	0.094	0.182
Inputs				
x_1	Labor‡	Number of employees	2,505	4,827.83
x_2	Capital‡	Physical capital	185,679.47	364,581.79
x_3	Purchased funds‡	All deposit categories	12,446,063.86	28,729,959.75
Input prices				
ω_1	Wages & salaries	Labor expenses/x_1	51.287	10.627
ω_2	Price of physical capital	(Amortizations+other noninterest expenses)/x_2	0.987	1.994
ω_3	Price of purchased funds	Financial costs/x_3	0.019	0.009

‡In thousands of euros.

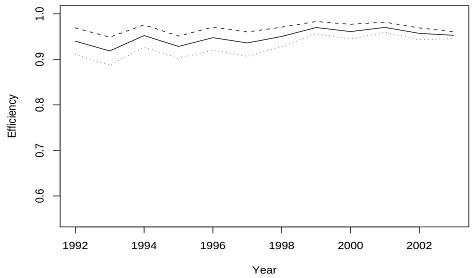
Table 2: Spearman correlation coefficients between cost and revenue efficiency, 1992–2003

Firms	Period	Correlation coefficient
Banking firms	1992–1995	0.621
	1996–1999	0.550
	2000–2003	0.464
Commercial banks	1992–1995	0.588
	1996–1999	0.467
	2000–2003	0.464
Savings banks	1992–1995	0.682
	1996–1999	0.750
	2000–2003	0.584

All coefficients significant at 1% level.

Figure 1: Evolution of mean efficiency, 1992–2003

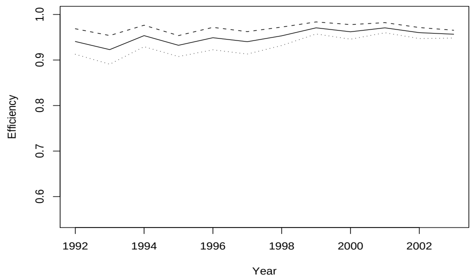
a) Cost efficiency



b) Input technical efficiency

c) Input allocative efficiency

d) Revenue efficiency



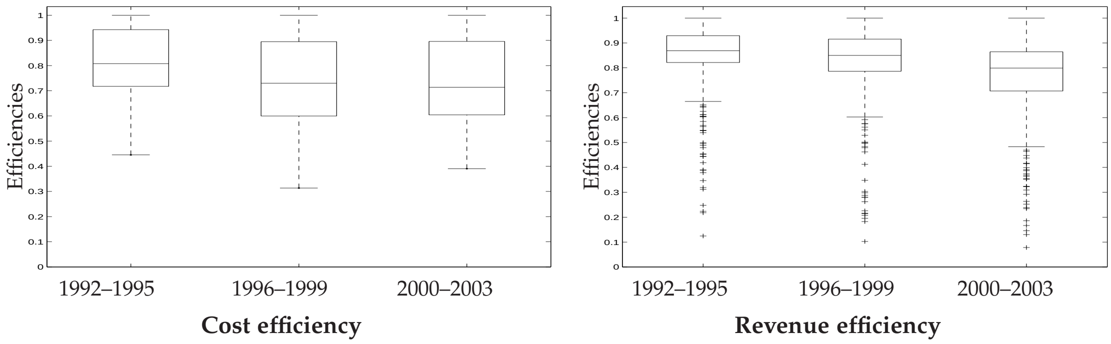
e) Output technical efficiency

f) Output allocative efficiency

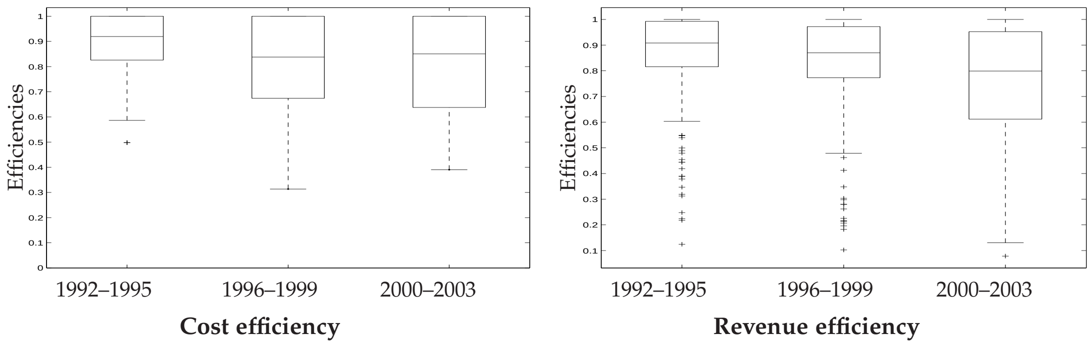
—— Banking firms ------ Commercial banks ······· Savings banks

Figure 2: Boxplots of banks' efficiencies

(a) Banking firms



(b) Commercial banks



(c) Savings banks

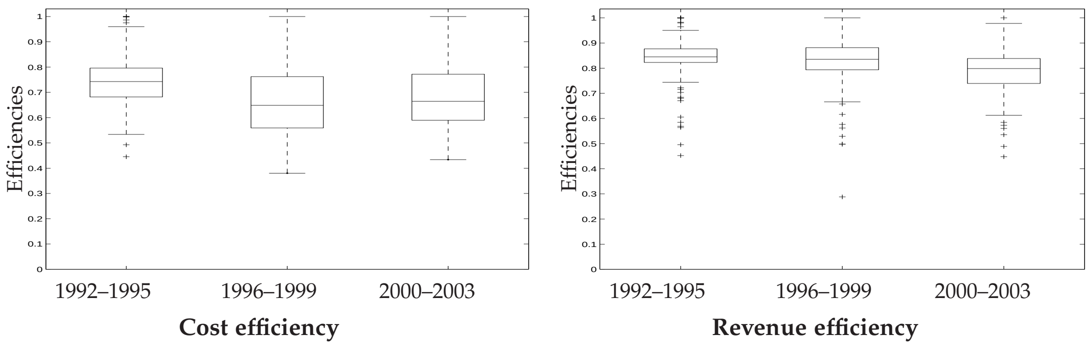
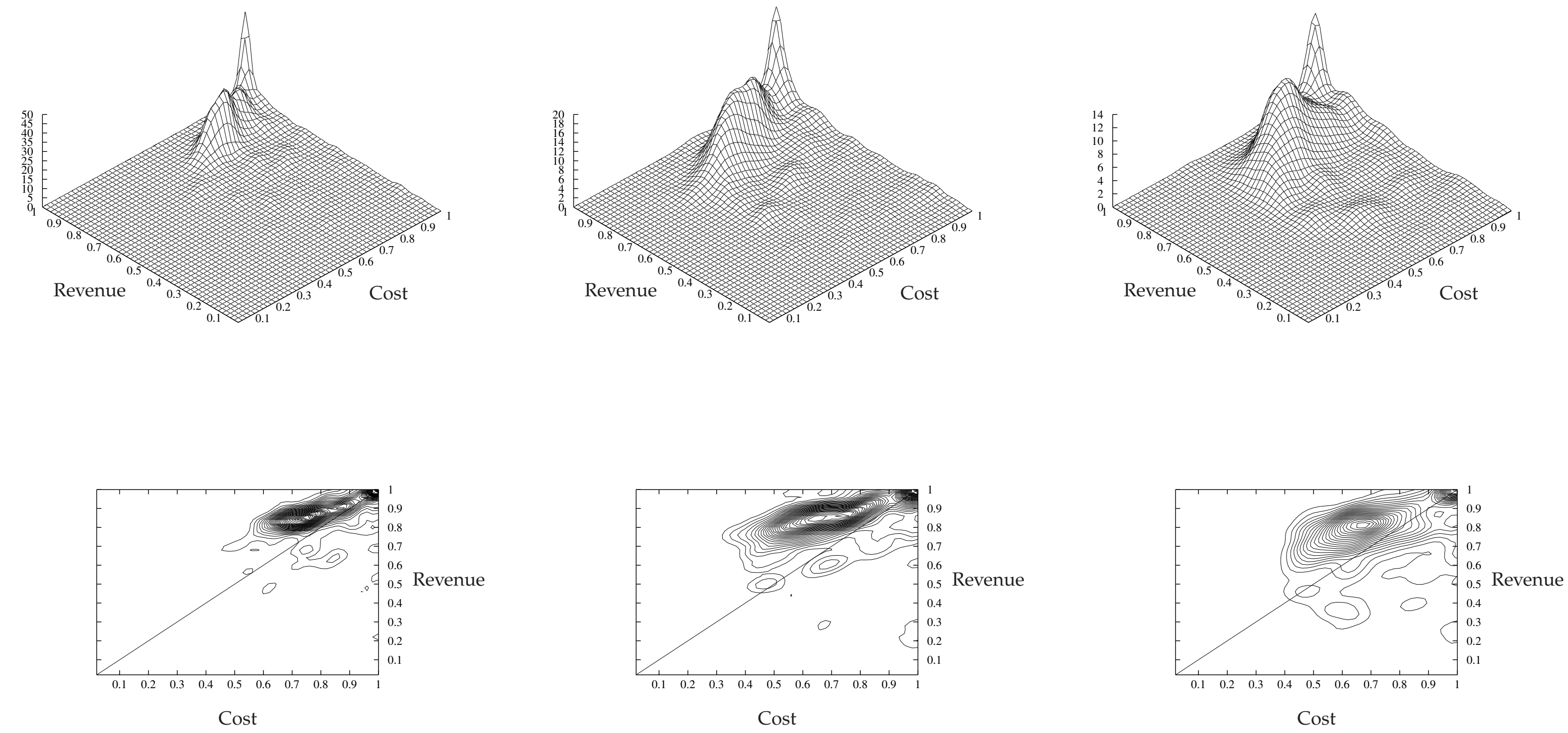


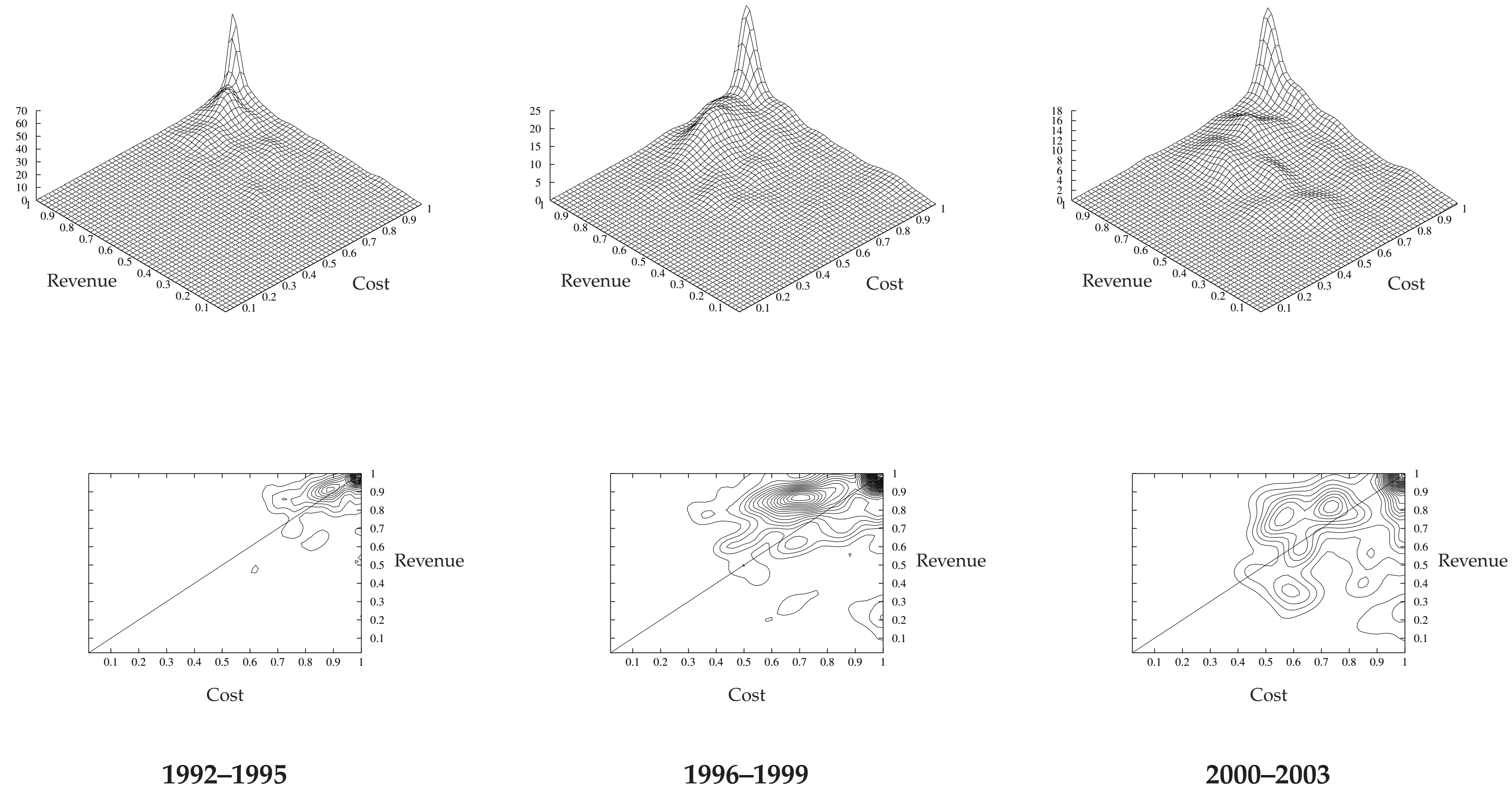
Figure 3: Joint densities for cost and revenue efficiency, banking firms (perspective and contour plots)



1992–1995 **1996–1999** **2000–2003**

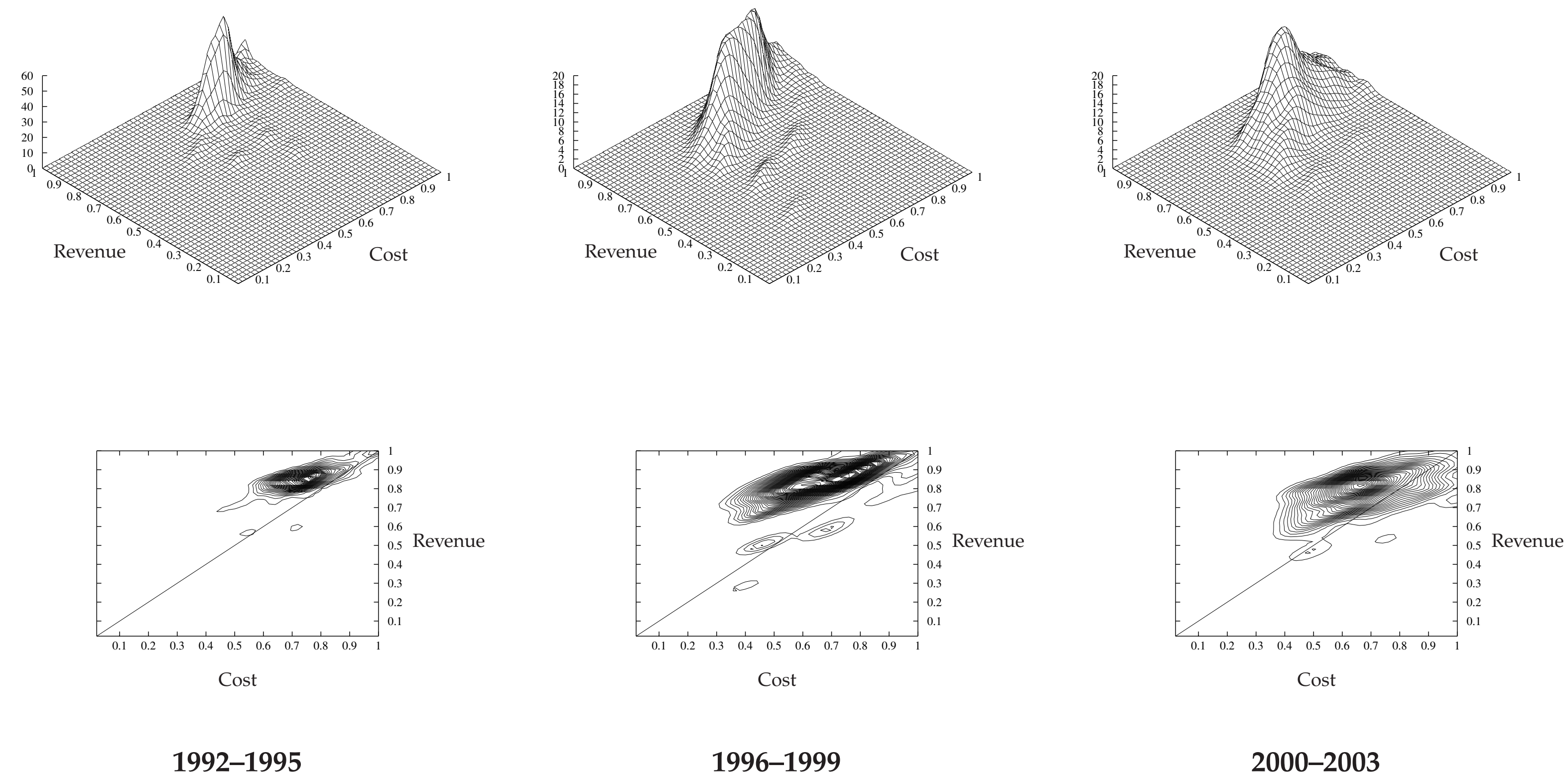
Densities estimated nonparametrically by means of Gaussian kernel. Bandwidth matrices (2 × 2) chosen according to Duong and Hazelton (2003).

Figure 4: Joint densities for cost and revenue efficiency, commercial banks (perspective and contour plots)



Densities estimated nonparametrically by means of Gaussian kernel. Bandwidth matrices (2 × 2) chosen according to Duong and Hazelton (2003).

Figure 5: Joint densities for cost and revenue efficiency, savings banks (perspective and contour plots)



Densities estimated nonparametrically by means of Gaussian kernel. Bandwidth matrices (2 × 2) chosen according to Duong and Hazelton (2003).