Mixed evidence? Revisiting the quiet life hypothesis in banking using nonparametric techniques*

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Abstract

Early studies testing the quiet life hypothesis in banking [Berger and Hannan, Review of Economics and Statistics LXXX (1998) 454–465] found strong evidence that banks in more concentrated markets exhibit lower cost efficiency levels. More recent studies have reexamined the issue in different contexts, with mixed results. These approaches are based on stipulating a linear relationship between market power and efficiency in banking, which might be problematic, as suggested by the literature on efficiency analysis. We explore how bank cost efficiency measures are related to market power using flexible techniques, which are more consistent with those employed to measure efficiency in the first stage of the analysis. Using as a laboratory the Spanish banking industry, results show that the relationship varies according to the level of market power, the component of efficiency evaluated (cost, technical or allocative) and the type of banking firm (commercial bank or savings bank), suggesting that the "quiet life" might be a reality only for some banks.

Keywords: banking, efficiency, market power, nonparametric regression, spline smoothing

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1. Introduction

Over the last twenty years, the changes and challenges faced by most banking industries worldwide have prompted a remarkable interest in analyzing several industrial organization (IO) topics in banking. Indeed, as suggested by Rhoades (1997), during the past fifteen years or so there has been more IO-related research in banking than many students of IO might expect. Some of the IO topics more profoundly examined in the banking literature relate to the structure-conduct-performance (SCP) paradigm (Bain, 1956), and the ensuing efficient-structure (ES) hypothesis (Demsetz, 1973). As reviewed by Berger *et al.* (2004), the early 1990s empirical banking studies analyzing the effects of concentration and competition were particularly concerned about whether the traditional SCP paradigm held for the U.S. banking industry. Although this literature is large, and despite the difficulties of summarizing results,[1] most studies found that banks in more concentrated local markets—as measured by the Herfindal-Hirschman Index (HII), or n-firm concentration ratio (CRn)—charged higher rates on loans, and payed lower rates on retail deposits (Berger and Hannan, 1989; Hannan, 1991).

Although most findings were consistent with the exercise of market power under the SCP hypothesis (Hannan and Berger, 1991; Neumark and Sharpe, 1992), it was not unusual to obtain weak relationships between concentration and profitability when firms' market shares were included in the regressions (Berger *et al.*, 2004). Therefore, paralleling the making in the IO literature, some studies aimed to analyze the validity of the ES hypothesis in banking—according to which high concentration endogenously reflects the market share gains of efficient firms (see Smirlock *et al.*, 1984). Typically, such studies controlled for measures of X-efficiency and scale efficiency, allowing concentration and market share to be functions of these efficiency measures (see, for instance, Berger, 1995). As for the SCP paradigm, the empirical evidence for the ES hypothesis was also weak.

In the context of the literature that analyzes the relationship between performance, market concentration and efficiency, other papers have focused on the study of the effect of market power on the managerial efficiency. In particular, the so called "quiet life"

[1] For a more thorough review, see the introductory article (Berger *et al.*, 2004) of the special issue of the *Journal of Money, Credit, and Banking* on bank concentration and competition.

hypothesis (Hicks, 1935) is considered a special case of the market power hypothesis. The quiet life hypothesis postulates that the higher market power, the lower the effort of managers to maximize operating efficiency, a negative correlation thus existing between market power and efficiency. In the empirical testing of this hypothesis, market concentration measures are traditionally used as proxy for market power (Berger and Hannan, 1998). However, as stated in Maudos and Fernández de Guevara (2007), recent studies show the limitations of using market concentration measures as indicators of banking competition[2] Therefore, they propose to use other indicators of competition such as the H-statistics (Panzar and Rosse, 1987), or the Lerner index (Lerner, 1934).

Our study analyzes the relationship between market power and efficiency considering an alternative to the traditional means used to evaluate the validity of either the SCP or ES hypotheses. Specifically, we employ nonparametric methods which are highly appropriate when a theory is lacking to evaluate the associations between two variables. Although theories are well established in our case, the mixed empirical evidence suggests they might be more difficult to test than one *a priori* might expect. Earlier initiatives, such as Clark (1986), considered similar issues. arguing that tests of the structure-performance paradigm yielded quantitatively small statistical significance because of the methodology employed. However, in contrast to a less restrictive nonparametric approach, his analysis was entirely confined to the parametric field, therefore disallowing more flexible interpretations of the relationship. Some recent contributions have also dealt with the quiet life hypothesis and related issues, among which we can highlight the papers by Koetter *et al.* (2011), Delis and Tsionas (2009), **?**Casu and Girardone (2009a), and Ariss (2010). Although their objectives are not exactly coincidental with those of Clark (1986), they do neither consider flexible techniques to examine the links between efficiency and market power like we do.

Our analysis is focused on the Spanish banking system, which offers a scenario where profound changes took place: important deregulations such as interest rate deregulation, total removal of legal coefficients, legal homogenization of both commercial and sav-

[2]See also Berger *et al.* (2004), Maudos and Fernández de Guevara (2004), Fernández de Guevara *et al.* (2005), Claessens and Laeven (2004), or Claessens and Laeven (2005).

ings 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 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. In this reshaped industry, in which tighter competition exists, an efficiency study is interesting, primarily because of the alleged inverse relationship between competition and inefficiency or, more exactly, X-inefficiency (Leibenstein, 1966). Accordingly, a considerable empirical effort has been devoted to analyze the competitive viability of Spanish banking firms, with mixed results.

The study proceeds as follows. The next section surveys the literature of the relationship between efficiency and competition. Section 3 presents the methodology used to measure market power and efficiency, emphasizing the relevance of focusing on cost efficiency and its technical and allocative components, introducing both the method and results on market power and efficiency separately. Section 4 describes the data and the specification of banking inputs and outputs. Section 5 presents the results. Finally, Section 6 concludes.

2. The relationship between efficiency and competition: the "quiet life" hypothesis

As it is mentioned in Maudos and Fernández de Guevara (2007), the literature on the relationship between competition and efficiency is related to the hypothesis that explains the relationship between market structure, efficiency and performance. According to the traditional structure-conduct-performance paradigm proposed by Bain (1956), firms in markets with higher concentration are able to earn extra profits as the result of collusion between the firms in the industry. Thus, this hypothesis postulates a positive relationship between performance and concentration, assuming that the higher the market concentration, the higher the firms' market power.

An alternative hypothesis establishes that the positive correlation between profitability and market concentration is spurious and simply proxies for the relationship between superior efficiency, gains in market share and, consequently, higher concentration. According to this efficient-structure hypothesis (Demsetz, 1973), the effect of concentration on profitability vanishes once a proxy variable for efficiency is introduced as explanatory variable.

In this context, the quiet life hypothesis focuses on the effect of market power on efficiency. This hypothesis postulates that the higher the market power, the lower the effort of managers to maximize efficiency, a negative correlation thus existing between market power and managerial efficiency.

Several are the reasons that can justify a positive relationship between higher levels of market power and lower efficiency levels (see Berger and Hannan, 1998). First, if firms can charge prices in excess to competitive levels, managers do not have incentives to work as hard to keep costs under control, enjoying a "quiet life". Second, market power may allow managers to pursue objectives other than revenue/profit maximization. Third, in a non-competitive environment, managers devote resources to obtaining and maintaining market power which raises cost and reduces cost efficiency. And fourth, market power allows inefficient managers' behavior to persist without any intention to pursue goals other than maximizing firm value.

There are several reasons that can justify a positive relationship between market power and efficiency (supporting the quiet life hypothesis), but there are also alternative explanations that can support the rejection of this hypothesis in the specific case of the banking industry. Taking into account the specific characteristics of the banking firms (asymmetric information, problems of adverse selection and moral hazard, etc.), banks can reduce these problems establishing long-term relationships with clients. As Petersen and Rajan (1995) demonstrate, banks with market power have lower costs of monitoring and transactions with borrowers, a positive relationship between market power and cost efficiency existing. Banks with market power may have cost advantages in screening certain groups of borrowers. In addition, market power allows banks to enjoy greater profits, which may create incentives to behave prudently, this behavior leading to the selection of less risky activities with lower monitoring costs. Finally, banks with market power are under less pressure to increase the quality of banking services, decreasing consequently the operating costs.

Although the relationship between profitability, market concentration and efficiency of the banking industry has been tested in an important number of papers, the available empirical evidence on the quiet life hypothesis is scarcer. However, in the last few years there is a renewed interest in analyzing the links between efficiency and market power. After reviewing this recent literature one may conclude that the empirical evidence is not conclusive—i.e., it is *mixed*.

Berger and Hannan's (1998) results are consistent with the quiet life hypothesis as a negative relationship between cost efficiency and market power (proxied by market concentration) is found for the U.S. banking industry. For a sample of developing countries, Ariss's (2010) results also support the quiet life hypothesis, considering that banks with more market power (proxied by the Lerner index) are also the most cost efficient. However, according to this author, one should be cautious about this result, if we consider that it is likely that the higher costs associated with market power are eventually channeled to bank clients which, in turn, may feed into higher prices and possibly boost bank profit efficiency. Similarly, Delis and Tsionas (2009), using a panel of EMU banks, report a negative relationship between cost efficiency and market power.

On the contrary, the papers by Maudos and Fernández de Guevara (2007), Koetter *et al.* (2011), Fu and Heffernan (2009) and Casu and Girardone (2009b) reject the quiet life hypothesis. The first paper analyzes the relationship between market power (the Lerner index) and cost efficiency for the EU-15 banking sector. Koetter *et al.* (2011) derive efficiency-adjusted Lerner indices for the U.S. bank holding companies. They conclude that the evidence on the relationship between competition and both cost and profit efficiency clearly rejects the quiet life hypothesis. Casu and Girardone (2009b) find positive causation between market power (proxied by the Lerner index) and efficiency for five EU banking sectors. Finally, for the Chinese banking system, Fu and Heffernan (2009) do not find evidence to support the quiet life hypothesis, although a drawback of this paper (as in Berger and Hannan's) is that they use market concentration as proxy variable for market power.

3. Methodology

3.1. The measurement of market power

There are basically two methodologies to measure the degree of competition in the banking industry.[3] The first one is the structural approach that stems from the traditional structure-conduct-performance paradigm and that uses market concentration indices as proxy variable for market power under the assumption that the higher the market concentration, the higher the market power. The second one is the so-called "New Empirical Industrial Organization" (NEIO) approach which relies on non-structural models that infer market power from the observation of banks' conduct. Under this approach, competition measures are developed from theory of the firm models under equilibrium conditions and typically use some form of price mark-up over a competitive benchmark. In the Lerner index,[4] it is the mark-up of price over marginal cost and the divergence of price from perceived marginal revenue for the Bresnahan's measure (see Bresnahan, 1989). The higher the mark-up, the greater the realized market power. An alternative approach, developed by Panzar and Rosse (1987)—the so-called H-statistic[5]—focuses on the degree to which changes in the input prices leads to subsequent changes in revenues provided that the industry in a long-run equilibrium.

As mentioned before, some contributions have shown the limitations of proxying bank competition intensity with concentration measures, pointing to the need of using alternative indicators. For this reason, we use a competition indicator from the new empirical industrial organization approach: the Lerner index.

The Lerner index measures the capacity to set interest rates above marginal costs as a proportion of prices. This market power indicator is usually derived from the Monti-Klein model (see Freixas and Rochet, 1997) and has been empirically approached in several papers cited above. As we interested in getting an aggregate measure of market power for

[3] See a recent survey in Carbó Valverde *et al.* (2009).

[4] The estimation of the Lerner index in banking has been applied in the studies by Angelini and Cetorelli (2003), Fernández de Guevara *et al.* (2005), Maudos and Fernández de Guevara (2004, 2007), Fernández de Guevara *et al.* (2007), Carbó Valverde *et al.* (2003), and Carbó-Valverde *et al.* (2009), among others.

[5] There is also an extensive literature that uses the Panzar and Rosse (1987) H-statistic. See for example, Bikker and Groeneveld (2000), De Bandt and Davis (2000), Claessens and Laeven (2004), among others.

the whole banking activity, we use the total assets of each bank as our proxy for banking output. With this approximation, the Lerner index is defined as the ratio "(price of total assets-marginal costs of total assets)/price". The price of total assets is computed from bank-level data as the ratio of bank revenue/total assets. Marginal costs are estimated from a translog cost function with a single output (total assets) and three inputs (deposits, labor and physical capital).

3.2. The measurement of efficiency

Efficiency may be measured via a variety of methods. They fall under the broad categories of parametric and nonparametric methods. Several monographs provide accurate descriptions of the available methods (see, for instance, Fried *et al.*, 1993, 2008). However, some relatively recent monographs lean towards either parametric (Lovell and Kumbhakar, 2000) or nonparametric methods (Färe and Grosskopf, 2004; Daraio and Simar, 2007). Some findings showing that results may differ greatly between parametric or nonparametric techniques might have deterred publication of new monographs describing both approaches.[6]

In addition to this, the evolution of parametric and nonparametric techniques has not been entirely equal. Up to the early nineties, both groups of techniques went through relevant progress,[7] but some of the most recent proposals have leaned towards the nonparametric field. Cazals *et al.* (2002) present a nonparametric estimator (order-m) which is more robust to extreme values than DEA (Data Envelopment Analysis) or FDH (Free Disposable Hull), similarly to the order-α estimator introduced by Daouia and Simar (2007). Some other recent proposals include Aragon *et al.* (2005), who present a nonparametric estimator of the efficient frontier based on conditional quantiles, or Martins-Filho and Yao (2007), who also propose a nonparametric model of frontiers which envelops the data and is also more robust to extreme values than previous methods.[8]

[6]The study by Murillo-Zamorano (2004) provide a relatively updated survey of the approaches to measuring efficiency and productivity using both parametric and nonparametric methods.

[7]The paper by Berger and Humphrey (1997) surveyed 130 articles applying frontier efficiency analysis to financial institutions in 21 countries, which considered either parametric or nonparametric techniques in similar proportions. Fethi and Pasiouras (2009) provide a more updated survey of this literature, although confined entirely to the nonparametric case.

[8]Some recent initiatives have also considered parametric approaches (see Murillo-Zamorano, 2004, , for

However, prices do enter the analysis using any of these new methods, and some of them carry difficulties in handling multiple outputs and multiple inputs. Yet in banking the availability of prices, and the multiple-input/multiple-output nature of the banking firms suggests previous nonparametric methods (such as DEA) may still be more advisable—at least until further progress is made in the aforementioned new fields of research. In addition, both the order-m (Cazals *et al.*, 2002) and order-α (Daouia and Simar, 2007) estimators, although presenting some relevant advantages with respect to DEA or FDH (summarized by Wheelock and Wilson, 2009), have also certain limitations partly derived from the need to specify the m (in the case of order-m) and α (in the case of order-α) parameters, which may be involved.

Therefore, the set of activity analysis techniques presented and 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. Accordingly, total costs will be defined as $\boldsymbol{\omega x} = \sum_{n=1}^{N} \omega_n x_n$. It is important to note that we are assuming 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

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

an interesting summary of Bayesian approaches to efficiency measurement). 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.

If $\boldsymbol{x}_s^*$ and $\boldsymbol{y}_s^*$ is the optimal input vector for firm s, $s = 1, \ldots, S$, cost efficiency *indexes* will be defined as $CE_s = \boldsymbol{\omega}_s' \boldsymbol{x}_s^* / \boldsymbol{\omega}_s' \boldsymbol{x}_s$. The indexes will be bounded by unity from above, i.e., efficient firms will be those with efficiency scores equal to one—or 100, if results were expressed as percentages.

Optimal values are found by solving linear programming problem. For cost efficiency, the linear programming problem (where $\mathbf{X}$ and $\mathbf{Y}$ are observed data) for each s firm is as follows:

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

3.3. Modeling the links between efficiency and market power

A mere cursory look at the empirical literature in most fields of economics reveals that a majority of applications use simple parametric approaches such as ordinary least squares (OLS) regression or two-stage least squares (2SLS) accompanied by simple descriptive statistics (DiNardo and Tobias, 2001). This approach resembles classical statistics, which are heavily based on parametric models—for example, observations are often regarded as a random sample from an underlying Gaussian distribution with an unknown mean and variance to be estimated from data. (Parametric) regression (especially OLS) has possibly been the most popular data-based technique for understanding the way two variables are related, especially for those cases falling into the "cause and effect" class.

OLS regressions assume the dependent variable of interest to be Gaussian distributed. But in our case, in which efficiency scores are bounded at unity, this assumption is clearly not met. The dependent variable must also be independently distributed. However, our efficiency scores are obtained using linear programming techniques and, therefore, this assumption is also violated, since firms' efficiencies are dependent in the statistical sense. This point has been forcefully made by Simar and Wilson (2007), Daraio and Simar (2005) and Balaguer-Coll *et al.* (2007). All these authors provide different solutions to these problems. The severity of this problem in the context of testing the quiet life hypothesis has been acknowledged by Koetter *et al.* (2011), who coincides in stressing how problematic it is to conditioning competition measures on banks' efficiency estimates obtained using frontier techniques—i.e., second-stage regressions using efficiency for the dependent variable lead to inconsistent and biased results.

The arguments in the previous paragraph would suffice *per se* to discard testing the quiet life considering OLS, or any of its variants—when efficiency scores have been obtained using linear programming techniques. In addition to this, the difficulties that the (scarce) previous empirical studies might have faced in testing the quiet life may relate to the fact that they use regression techniques which focus on the *average* effect for the *average* bank. However, as indicated by Reichstein *et al.* (2010), there are cases in which "the devil might dwell in the tails", i.e., the sign and significance of a given coefficient might be driven by the behavior of few firms. Therefore, there are some circumstances under which OLS is not the most appropriate, and some alternatives which are more flexible and consider the entire distributions of efficiencies and their dependence of market power are better.

In addition to the rationale provided above, although using linear models may generally represent a valid alternative, sometimes their choice entails a fair preliminary approach and can be very restrictive, leading to departures from reality. Indeed, in econometrics, the assumption of statistical adequacy, or correct model specification has often constituted an important concern, and functional forms misspecified may lead to invalid tests for the hypotheses under discussion (i.e., the so-called "parametric straitjacket"). There are circumstances in which transformations and/or quadratic terms can be used to handle nonlinearities, but it should be kept in mind that their use can require a good deal of expertise and time. Therefore, it remains an open question as to why more flexible methods—such as nonparametric regression—are still far from overused by economists, despite the recent (and not so recent) advances in this field by both the statistics and econometrics' literatures (DiNardo and Tobias, 2001).

Nonparametric regression[9] allows us to understand how some variable of interest, in our case the efficiency (Y or, in our particular setting, EFF) of any particular decision unit, is affected by variations in some other variable X. The utmost advantage of this type of technique—compared to *parametric* methods such as linear or polynomial regression—is its absence of *a priori* assumptions concerning the particular functional form on the link between Y and X.

As suggested by Jennen-Steinmetz and Gasser (1988), out of the three best-known estimators of the nonparametric regression problem—smoothing splines, k-nearest neighbor estimator, and kernel estimators—the large body of theoretical results regarding asymptotic properties of these estimators has so far not solved the problem as to which method is always best and, if not, under which circumstances each method is preferable.[10] Several comparative studies exist such as Jennen-Steinmetz and Gasser (1988) and, in an application to Engel curves estimation, see Engel and Kneip (1996). A comparison among the three most popular and easy-to-implement methods, namely, the kernel, the k-nearest neighbor, and the (cubic) spline smoothers, is performed in Härdle (1990), both in theoretical and empirical terms. Silverman (1984) has demonstrated that spline smoothing corresponds approximately to smoothing by a kernel method with bandwidth depending on the local density of design points.

Although some studies consider a variety of nonparametric techniques claiming for their advantages when applied to economic and financial problems (see, for instance Engel and Kneip, 1996), wide acceptance has not been achieved in these research areas. Whereas one may find some applications of kernel regression, spline smoothing approaches are scarcer (see, for instance, Bao and Wan, 2004).

The underpinnings of nonparametric regression methods can be found elsewhere (see, for instance Li and Racine, 2007), yet we provide some insights to make the exposition

[9] Some recent and not-so-recent monographs cover this topic; see, for instance, Härdle (1990) or, more recently, Li and Racine (2007).

[10] In addition, although many different methods have been proposed to construct nonparametric estimates of a smooth regression function, the attention devoted to the different smoothing methods has not been great. Among them, the kernel, k-nearest neighbor ($k - NN$), orthogonal series and spline estimators have received far more attention than some others such as recursive techniques, the regressogram, convolution smoothing, median smoothing, split linear fits or empirical regression which notwithstanding represent satisfactory choices in some specific cases (see Härdle, 1990).

as self- contained as possible. For a particular data set $\{(X_s, Y_s)\}_{s=1}^{S}$, we are interested in estimating the mean response curve m:

$$Y_s = m(X_s) + \varepsilon_s, \; s = 1, \ldots, S. \tag{5}$$

It is often difficult to ascertain the particular nature of $m(\bullet)$, i.e., to know whether the relationship is linear, quadratic, growing in X, etc. In such cases nonparametric regression advantages turn out to be especially relevant.

We use a particular variant of nonparametric regression, namely, smoothing splines, which provide a seamless link with semiparametric approaches to regression. Other studies such as Bao and Wan (2004) have used this alternative, considering that in some circumstances the underlying theories are not capable of conveying sufficient information to enable a correct and successful specification of parametric models. The *penalized* (or p-splines) variant to smoothing splines (Ruppert and Carroll, 2000) introduces a penalty to control for possible spatial heterogeneity in the regression function. Similarly to kernel regression, m in Equation (5) is assumed to be a smooth function equal to the conditional mean of y_s given x_s, which is estimated using a regression spline model:

$$\widehat{m}(x; \boldsymbol{\beta}) = \beta_0 + \beta_1 x + \ldots + \beta_p x^p + \sum_{k=1}^{K} \beta_{p+k}(x - \kappa_k)_+^p. \tag{6}$$

Splines are essentially piecewise polynomials whose different polynomial segments are tied together at a series of knots in a way that insures certain continuity properties (Bao and Wan, 2004). In Equation (6) the knots are represented by $\kappa_1, \kappa_2, \ldots, \kappa_K$, whereas $p \geq 1$ is an integer, $\boldsymbol{\beta} = (\beta_0, \ldots, \beta_p, \beta_{p+1}, \ldots, \beta_{p+K})^\top$, with β_p the coefficient of the p^{th} knot, is a vector of regression coefficients, and $(u)_+^p = u^p I(u \geq 0)$. Since the number of knots determines whether the fit may be too rough, or too smooth (too many knots yield quite a rough fit), it may be relevant to constrain their influence. Penalized spline regression provides means for doing so, hoping to result into a less variable fit.

Equation (6) represents a spline model of general degree (i.e., a p^{th}-degree spline) in which, using truncated power functions, the basis is:

$$1, x, \ldots, x^p, (x - \kappa_1)_+^p, \ldots, (x - \kappa_k)_+^p,$$

which is known as the truncated power basis of degree p. When p is odd, a set of basis functions spanning the space of p^{th}-degree polynomials with knots at $\kappa_1, \ldots, \kappa_K$ is

$$1, x, \ldots, x^p, |x - \kappa_1|^p, \ldots, |x - \kappa_k|^p.$$

Smoothing splines have a natural representation in terms of this type of functions, sometimes called radial basis functions (Ruppert *et al.*, 2003). Specifically, we consider the cubic smoothing spline:

$$\widehat{m}(x; \boldsymbol{\beta}) = \beta_0 + \beta_1 x + \sum_{k=1}^{K} \beta_{1k} |x - \kappa_k|^3 \tag{7}$$

where $\hat{\beta}_0, \hat{\beta}_1$ and $\hat{\beta}_{11}, \ldots, \hat{\beta}_{1K}$ minimize

$$||\mathbf{y} - \mathbf{X}_0 \boldsymbol{\beta}_0 - \mathbf{X}_1 \boldsymbol{\beta}_1||^2 + \lambda^3 \boldsymbol{\beta}_1^\top \mathbf{K} \boldsymbol{\beta}_1 \tag{8}$$

for some $\lambda \geqslant 0$, subject to

$$\mathbf{X}_0^\top \boldsymbol{\beta}_1 = \mathbf{0}, \tag{9}$$

where $\boldsymbol{\beta}_0 \equiv [\beta_0, \beta_1]^\top$, $\boldsymbol{\beta}_1 = [\beta_{11}, \ldots, \beta_{1K}]^\top$, $\mathbf{X}_0 = [1, x_i]_{1 \leq i \leq n}$, and:

$$\mathbf{X}_1 = \left[|x_i - \kappa_k|^3 \right], \; \mathbf{K} = \left[|\kappa_k - \kappa_{k'}|^3 \right]$$

This is accomplished by specifying a knot sequence $\kappa_1, \ldots, \kappa_K$ using the basis functions $1, x, |x - \kappa_1|^3, \ldots, |x - \kappa_K|^3$ (Ruppert *et al.*, 2003). λ is a smoothing parameter which controls the trade-off between smoothness, and goodness of fit to the data. The larger the value of γ, the more the data will be smoothed to produce the curve estimate. $\lambda^3 \boldsymbol{\beta}_1^\top \mathbf{K} \boldsymbol{\beta}_1$ is called a *roughness penalty* because it penalizes fits that are too rough, thus yielding a smoother result. We have followed Ruppert *et al.* (2003) regarding the choice of smoothing parameter and knots' position.

4. Data, inputs, and outputs

The data used in the article 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.[11] 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 additional 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. The banks for which either missing or unreliable information (zero employees, etc.) were excluded from the study. Our sample represents more than 90% of total industry assets.

Specifying inputs and, especially, outputs, is often a controversial issue in banking. On the input side, our choice 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. There exist three basic approaches to *define* bank output, namely, the asset, user cost, and value-added approach (Berger and Humphrey, 1992; Tortosa-Ausina, 2002). 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

[11] In 2005 there was a regulatory change so that bank public data are now published following a very different decomposition of the balance sheet items. There have been no institutional initiatives so far to provide a homogeneous database covering the years before and after 2005. We chose the pre-2005 period because it allows to include more years in the study.

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.[12]

5. Results

5.1. Results on market power

Figure 1 displays boxplots on the evolution of market power for all banking firms, commercial banks, and savings banks. They show that market power has been increasing over time, regardless of the type of firm under analysis. However, several specificities emerge. Considering the entire banking industry (Figure 1.a), the median (the horizontal line inside each box) indicates that market power has been increasing over the sample period. However, there is still a remarkable number of outliers which, technically, are those observations beyond the upper and lower whiskers.[13] Although more than 50% of banking firms have Lerner indices above 0.4 in the 2000–2003 period, this did not occur in the preceding years. However, there is a remarkable number of firms whose market power is quite low, as indicated by the high number of observations below the lower whisker. In sum, although this is a hypothesis which need to be tested properly, the distribution of

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

[13] Specifically, 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 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.

the Lerner index is *stretching* over the sample period, indicating that the new competitive and regulatory environment has had a relatively strong impact on market power.

The reasons explaining this evolution are multiple, and lie beyond the scope of this paper (see, for instance Maudos and Pérez, 2003). However, some of them could be related to the differing trends found for commercial banks and savings banks. As indicated in Figure 1.b, there is a remarkable amount of variability for commercial banks, whose boxplots indicate that the distance between the tails of the distribution is increasing. And this is not only attributable to the behavior of the observations at both extremes of the distribution, since the central 50% of the probability mass (the "box") has also become bigger.

In contrast, savings banks show a different pattern. The short distance between the whiskers indicate that homogeneity prevails among this group of banking firms. This is a relatively surprising finding, since the deregulatory initiatives (Grifell-Tatjé and Lovell, 1996; Tortosa-Ausina *et al.*, 2011) have enabled commercial banks and savings banks to face the same regulatory environment—they only differ in their type of ownership (Crespí *et al.*, 2004). However, discrepancies among savings banks in many fields (in this case, in terms of market power) are still minor.

We can consider a proper test in order to elucidate whether the differences among the different types of institutions are significant or not. Table 2 provides results on the Li (1996) test in order to ascertain whether results differ according to a variety of hypotheses, namely, we test whether market power *distributions* differ significantly when comparing both types of firms, and when comparing the different types of firms over time—i.e., 1992 vs. 2003, for which the relevant hypotheses are $H_0 : f(\cdot) = g(\cdot)$, where f and g represent the relevant distributions. Details on the specifics of the test are provided not only in Li (1996) but also in other applications such as Kumar and Russell (2002) or Balaguer-Coll *et al.* (2010). In brief, it consists of comparing two distributions based on kernel methods, making no assumptions on the shape of the distributions, and focusing on their entirety rather than simple summary statistics such as ANOVA, Kruskal-Wallis or Wilcoxon and related tests do. This is important because the average may mask important trends at firm level.

Results show that differences are always significant at the 1% significant level. When comparing commercial banks and savings banks, the null hypothesis of equality of distributions ($f(Lerner^{\text{Commercial banks}}) = g(Lerner^{\text{Savings banks}})$) is strongly rejected. When comparing the distributions of the Lerner index at the initial and final sample years (1992 and 2003), although the test statistics are lower, the null hypothesis is also rejected at the usual significance levels, for all banking firms ($f(Lerner^{\text{Banking firms, 1992}}) = g(Lerner^{\text{Banking firms, 2003}})$), commercial banks ($f(Lerner^{\text{Commercial banks, 1992}}) = g(Lerner^{\text{Commercial banks, 2003}})$) and savings banks ($f(Lerner^{\text{Savings banks, 1992}}) = g(Lerner^{\text{Savings banks, 2003}})$).

5.2. Results on efficiency

Figure 2 displays results for cost, 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 similar to those 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.

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 they can perform the same operations,[14] cost efficiency differences, on average, are

[14]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

not fading away.

The decomposition of cost efficiency into their technical and allocative components is quite revealing, since the sources of inefficiency are identified. Technical efficiency (see Figure 2.b) is remarkable, 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. On the other hand, allocative efficiency (Figure 2.c), 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 on cost efficiency are displayed in Figure 3 for all types of banking firms. Considering the banking industry as a whole, Figure 3(a) indicates that discrepancies are important on the cost side, and they increase over time. 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 3(b) and Figure 3(c). Differences among commercial banks increase rapidly; on the other hand, savings banks' behavior is much more homogeneous, although differences seem also to be growing.

5.3. On the causality between efficiency and market power

The links between market power and the variety of efficiency concepts considered here are explored in figures 4–6 which show results on the links between efficiency and market power, for all cost, technical, and allocative efficiency and using penalized spline smoothing. We provide standard error bands—in particular, pointwise ± 2 std. error bands—which provide a more precise view of the probability mass supporting the sign

insights on the peculiar ownership type of Spanish savings banks.

of the relationship. All estimations have been performed for the entire 1992–2003 period. Each figure contains three panels: banking firms, commercial banks, and savings banks. We have performed the analysis separately because, while it is true that both types of firms face the same regulatory environment and can perform exactly the same operations, strategies to respond to deregulation have differed a great deal.

When considering the relationship between market power and cost efficiency estimated via spline smoothing (Figure 4), the difficulties of fitting a linear model are blatant due to the apparent nonlinearity of the relationship. When all banking firms are considered (Figure 4.a) the link shows a U-inverted functional form. For low levels of the Lerner index, the relationship is found to be **positive**, yet the wide standard error bands suggest significance is low. However, an inflection point is observed in the vicinity of $Lerner \approx 0.2$, when considering banking firms as a whole, and the regression line turns negative. Although the relationship between market power and cost efficiency becomes positive for high values of the Lerner index, the wide standard error bands, and also the number of observations (which are displayed on the OX axis using short vertical bars) indicate that behavior is caused by very few observations, therefore not providing statistical support to this claim. Therefore, Figure 4.a gives support to these techniques as a relevant tool for testing the quiet life, since the negative relationship (supporting the "quiet life") does not hold for the entire conditional distribution.

Results vary a great deal if performing the analysis separately for commercial banks and savings banks. As suggested by Figure 4.b, cost efficiency has no apparent links with market power for commercial banks, as shown by the standard error bands. Therefore, the empirical evidence would be too weak either to support or reject the quiet life. Figure 4.c, on the other hand, suggests that the negative relationship found is mostly driven by savings banks.

As revealed by figures 5 and 6, the patterns found for cost efficiency are mostly driven by their allocative components. The trend is apparent for either type of firm. In the case of technical efficiency, the sign of the relationship is mostly **positive** regardless of the type of firm under analysis, but especially for savings banks—which also showed the clearest tendencies for cost efficiency. In the case of banks, although the trend is unsteady, for the bulk of observations—ranging in the *Lerner* $\in (0.2, 0.5)$ interval—the relationship is also positive. Therefore, allocative efficiency would be the main source for the types of relationships found for cost efficiency. As suggested in figures 6, the shape is clearly *U*-inverted for commercial banks (especially for revenue efficiency) and mostly negative for savings banks.

6. Concluding remarks

Although several studies have analyzed the relationship between market power and efficiency in banking, the empirical evidence obtained to date is not conclusive. On the one hand, the studies by Berger and Hannan (1998), Delis and Tsionas (2009) and Ariss (2010) support the "quiet life" hypothesis, according to which managers would translate higher inefficiencies into higher prices—as opposed to the efficient structure paradigm, where best practice allows firms to earn market power. On the other hand, papers by Maudos and Fernández de Guevara (2007), Casu and Girardone (2009a), Fu and Heffernan (2009), and Koetter *et al.* (2011) reject that hypothesis.

Despite the view that the relationship between competition and efficiency is complex is becoming increasingly popular, there have been no attempts to explore the relationship assuming more flexible approaches, postulating no *a priori* relationship between market power and efficiency, which is precisely what we do in this paper. Specifically, we consider nonparametric regression techniques, which are appropriate in our particular setting not only because of their flexibility, but also because they do not confine the analysis to the average effect for the average bank, and for representing an alternative to OLS which "are invalid in this context due to complicated, unknown serial correlation among the estimated efficiencies" (Simar and Wilson, 2007).

Using the Spanish banking sector as laboratory, our results show that there are remarkable differences between commercial banks and savings banks' market power indicators, and also between the efficiencies found for both types of firms. In contrast to most previous studies, we conduct some tests which enable to conclude whether differences between the types of firms are significant or not. However, the most remarkable finding is that, for the entire banking industry, the relationship between market power (measured using a non-structural indicator of the degree of market competition such as the Lerner index) and efficiency is *not* linear. The parameter that shapes the relationship between both variables is not constant along the distribution, indicating that the significance market power's impact on efficiency varies for each firm.

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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
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: Distribution hypothesis tests[a] (Li, 1996) (1992–2003)

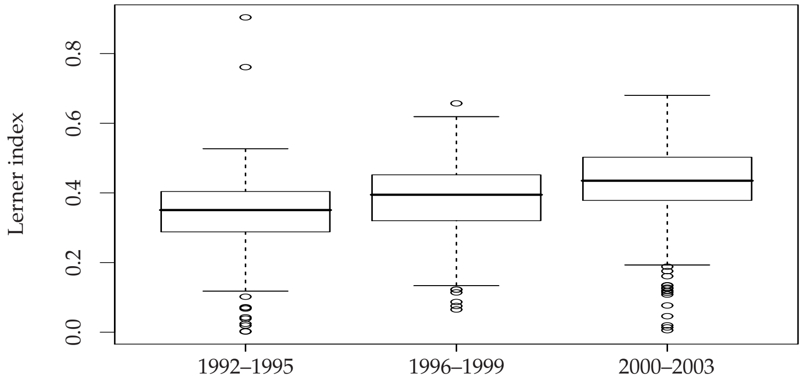
Null hypothesis (H_0)[b]	T-test statistics	1-Percent significance level (critical value=2.3263)
$f(Lerner^{\text{Commercial banks}}) = g(Lerner^{\text{Savings banks}})$	33.5789	H_0 rejected
$f(Lerner^{\text{Banking firms, 1992}}) = g(Lerner^{\text{Banking firms, 2003}})$	17.1974	H_0 rejected
$f(Lerner^{\text{Commercial banks, 1992}}) = g(Lerner^{\text{Commercial banks, 2003}})$	3.4918	H_0 rejected
$f(Lerner^{\text{Savings banks, 1992}}) = g(Lerner^{\text{Savings banks, 2003}})$	15.9216	H_0 rejected

[a] Notes: $f(\cdot)$ and $g(\cdot)$ are (kernel) distribution functions for market power.

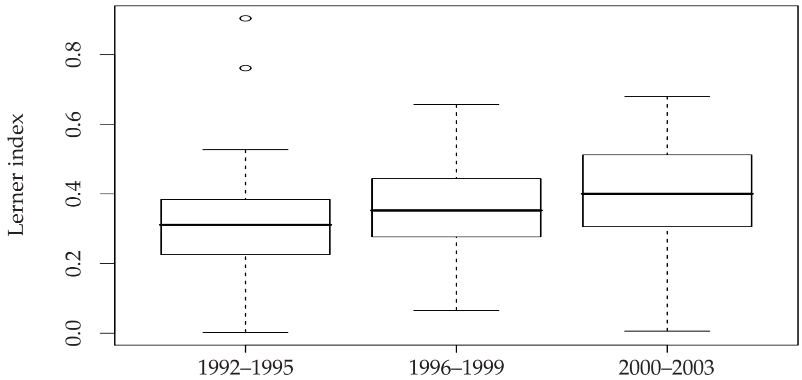
[b] The null hypothesis tests for the equality of distributions $H_0 : f(x) = g(x), \forall x$, against the alternative, $H_1 : f(x) \neq g(x)$, for some x.

Figure 1: Boxplots for market power (Lerner index), 1992–2003

(a) Banking firms



(b) Commercial banks



(c) Savings banks

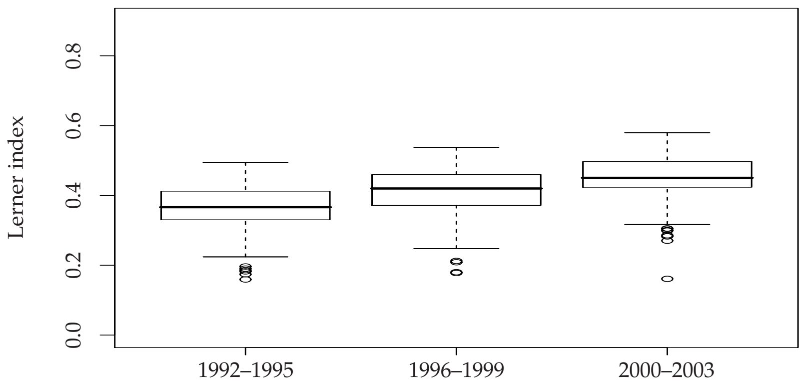
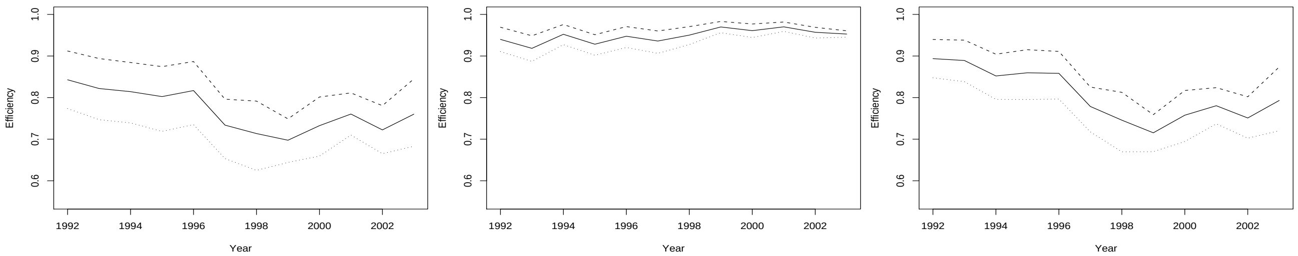


Figure 2: Evolution of mean efficiency, 1992–2003

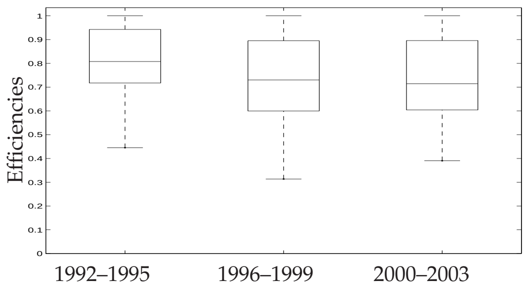


(a) Cost efficiency **(b)** Technical efficiency **(c)** Allocative efficiency

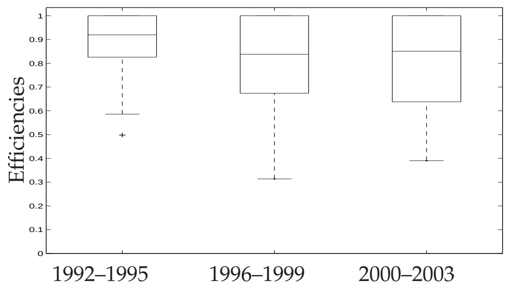
—— Banking firms ------ Commercial banks ······ Savings banks

Figure 3: Boxplots of banks' cost efficiency

(a) Banking firms



(b) Commercial banks



(c) Savings banks

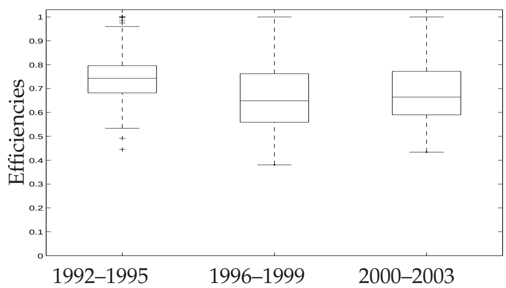
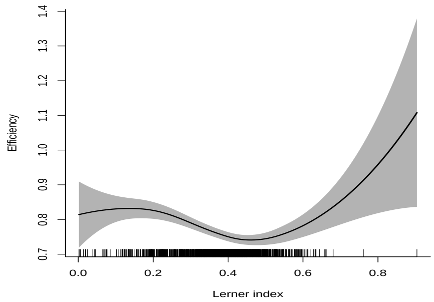
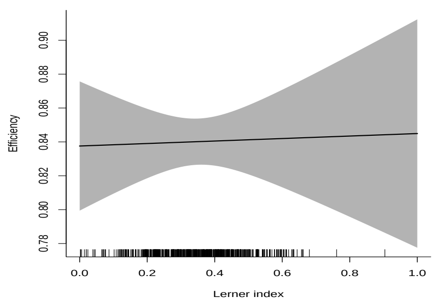


Figure 4: Cost efficiency vs. market power (Lerner index), spline smoothing regression (1992–2003)

(a) Banking firms



(b) Commercial banks



(c) Savings banks

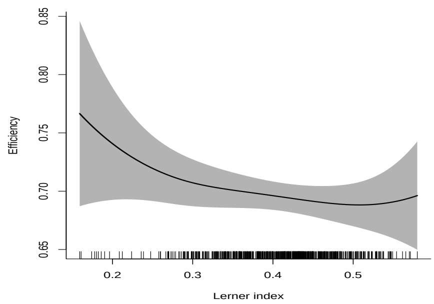
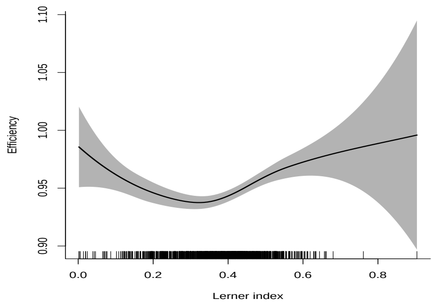
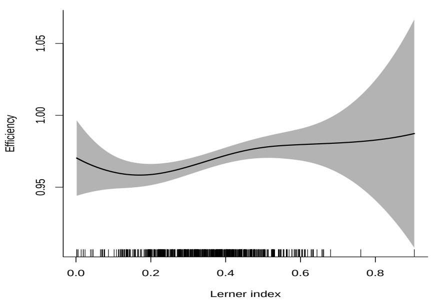


Figure 5: Technical efficiency vs. market power (Lerner index), spline smoothing regression (1992–2003)

(a) Banking firms



(b) Commercial banks



(c) Savings banks

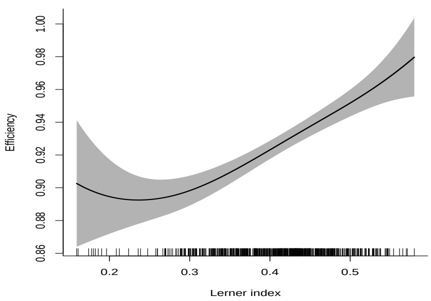
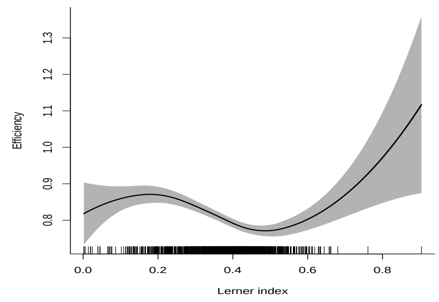
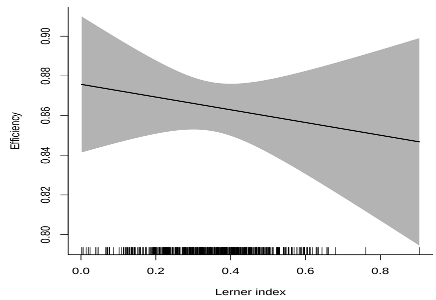


Figure 6: Allocative efficiency vs. market power (Lerner index), spline smoothing regression (1992–2003)

(a) Banking firms



(b) Commercial banks



(c) Savings banks