DOCTORAL THESIS

Novel Perspectives on Technology-Based Efficiency and Productivity Analyses

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To my parents and my aunt,

the best role models one could ask for.

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Abstract

This dissertation contributes to the efficiency and productivity literature by adopting a managerial focus to address gaps in previous research. In doing so, it uses existing methodological tools, further developed and adapted to current needs. These proposals are applied to the Spanish banking sector, an industry that attracted vast amounts of interest due to its post-deregulation growth phase. Against the background of the recent financial crisis, this attractiveness for research of (Spanish) banks will probably escalate, as new consolidation policies from central institutions will induce novel competitive strategies.

Three topics represent the core chapters of this thesis: (1) The identification and analysis of bank performance groups through decomposed productivity and efficiency indicators; (2) New proposals of total factor productivity (*TFP*) benchmarking via technology-based index numbers; (3) The assessment of potential gains from mergers and acquisitions (*M&As*) through convex and non-convex efficiency frontiers.

In the framework of the strategic groups' literature, the first chapter analyses changes in the productivity and efficiency of Spanish private and savings banks between 1998 and 2006. By adapting a decomposition of the Malmquist productivity indices, it proposes similar components decomposing the Luenberger productivity indicator. *TFP* is disentangled into technological and efficiency changes. The latter is then decomposed into pure efficiency, scale and congestion changes. Empirical results show that productivity improvements are partially due to technological innovation and explain how the competition between private and savings banks develops. Consequently, the Luenberger components are used as cluster analysis inputs. Thus, economic interpretations of the resulting performance groups are made via key differences in *TFP* components. To end with, as suggested by the strategic groups' literature, insights are gained by linking these performance groups with banking ratios.

Second, by proposing a benchmarking framework to analyze *TFP*, a gap is filled between the benchmarking literature and multi-output efficiency and productivity studies. Different specifications of the Hicks-Moorsteen *TFP* index are tailored for specific benchmarking perspectives: (1) static, (2) fixed base and unit, and (3) dynamic *TFP* change. These approaches assume fixed units and/or base technologies as benchmarks. In contrast to most productivity indices, the standard Hicks-Moorsteen index always leads to feasible results and *TFP* interpretations. Through the defined specifications, managers can assess different facets of the firm's strategic choices in comparison with relevant benchmarks and thus have a broad background for decision making. An analysis for the Spanish banking industry between 1998 and 2006 illustrates the feasibility and managerial implications of the proposed framework.

The third chapter scrutinizes the potential efficiency gains from *M&As*, a widely researched topic, but often linked to inconclusive results. We speculate that this is partly caused by the employed methodological assumptions. Among them, the assumption of a convex technology can be an important influence on the results. Thus, both convex and non-convex technologies are used to reveal post-*M&As* cost excess gains due to scale and technical inefficiencies. Ex ante conditions for achieving potential cost reductions are devised and then tested ex post on a sample of 32 Spanish banking *M&As* that occurred between 1988 and 2006. Empirical results show that significant cost excess reductions appear two years after the merger event. Furthermore, it is illustrated that the non-convex estimations are closer to the movements in the observed costs. These are interesting findings in view of the upcoming merger wave and should be complemented with research on scope efficiency and economies of diversification.

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General Introduction

1. Brief Description of Research Antecedents and Current Developments

Academic literature on the efficiency and productivity of banking industries has attracted vast amounts of interest (see, *e.g.*, the surveys in Berger and Humphrey (1997) or Goddard *et al.* (2001)). Accordingly, the efficiency of the Spanish banking sector has been scrutinized through a wide array of research perspectives (see, *e.g.*, Grifell-Tatjé and Lovell 1996, 1997a, b; Lozano-Vivas 1997; Prior 2003; Tortosa-Ausina 2003, 2004; Cuesta and Orea 2002; Carbó-Valverde and Humphrey 2004; Crespí *et al.* 2004; Zúñiga-Vicente *et al.* 2004; Más-Ruiz *et al.* 2005; Prior and Surroca 2006; Tortosa-Ausina *et al.* 2008, to name just a few).

This nexus between efficiency analyses and Spanish banking exists due to the characteristics of the industry and the theoretical underpinnings of the employed methods. Moreover, recent efficiency and productivity research and banking industry developments call for new methodological proposals to fill existing literature gaps. Even if the prior research is extensive, identified gaps include the analysis of performance (or strategic) groups, benchmarking methodologies and the assessment of gains from mergers and acquisitions (*M&As*). These are thoroughly explained in Section 2, which describes the specific research objectives and contributions.

Non-parametric efficiency and productivity frontier methods have experienced an important upsurge in popularity. This is because they do not require input or output prices (information which is not always available), but rather rely on physical inputs and outputs solely. In addition, these can act in multi-objective environments with no a priori restrictions on the mathematical formula for a specific production function or a specific distribution assumption for the residuals.

Probably the best-known non-parametric estimation method is the Data Envelopment Analysis (*DEA*) (see Färe *et al.* (1994) or Ray (2004) for theoretical specifications). In *DEA* one computes the degree of inefficiency separating a certain Decision Making Unit (*DMU*) from the efficiency frontier shaped by the industry's best practices. These frontiers are based on approximations of true but unknown technologies. To form the efficient frontier, relative comparisons are computed between each *DMU* and the analyzed sample, thus identifying efficient benchmarks corresponding to inefficient *DMUs*. As stated by Berger and Humphrey (1997: 175): "at its heart, frontier analysis is essentially a sophisticated way to benchmark the relative performance of production units". Furthermore, *DEA* scores are easy to interpret since they employ a model with an economic underpinning in production theory. The outcomes simply show the percentage of output increase or input decrease needed to reach the efficiency frontier.

DEA computations provide snapshots (*i.e.* cross-sections) of efficiency measurements. In inter-temporal analyses, the efficiency and productivity literature captures the potentially shifting efficiency frontier usually through *DEA*-based index numbers. For instance, the geometric mean Malmquist productivity index, probably the best-known measure of this type, has been extensively used in past research (see the surveys of Färe *et al.* 1998 or, more recently, Fethi and Pasiouras 2010).

There are however a few pitfalls to the use of these well-known measures. These drawbacks can lead the way towards new proposals via existing or innovative specifications. First, the Malmquist index has a suitable interpretation for the academic community due to its ratio-based formulation. Nonetheless, the business and accounting communities are more familiar to evaluating cost, revenue, or profit differences (Boussemart *et al.* 2003). A solution may be the use of the scarcely employed Luenberger indicator (Chambers 2002). This indicator is compatible with the goal of profit maximization, while the Malmquist indices normally focus on either cost minimization or revenue maximization (Boussemart *et al.* 2003). In addition, Malmquist indices are known to overestimate the productivity change as opposed to the Luenberger indicators (see Boussemart *et al.* 2003; Managi 2003).

Second, most indices and indicators have infeasibilities problems. While these are not crucial when performing sample-level analyses, they become vital for *DMU*-level investigations (such as benchmarking). Thus, new applications of this type should consider using measures that are always well-defined. A viable alternative is given by the Hicks-Moorsteen index (Bjurek 1996). As Briec and Kerstens (2010) demonstrate, the Hicks-Moorsteen productivity index satisfies the determinateness property under mild conditions. What's more, the Hicks-Moorsteen index has a total factor productivity (*TFP*) interpretation, an aspect where the Malquist index has shortcomings (see Grifell and Lovell 1995). Also, as in the case of the Luenberger indicator, the Hicks Moorsteen is a simultaneously output- and input-oriented index.

Third, when evaluating ex post gains (*e.g.* for events as *M&As*), the technology frontier approximation should be as precise as possible. There are two main alternatives to shaping the efficiency frontier. These either assume a convex technology (*i.e. DEA*) or a non-convex technology (*i.e.* Free Disposal Hull (*FDH*)) (see Ray (2004) for theoretical specifications). The convex assumption is by far more popular and can be encountered in the majority of frontier applications. Nonetheless, non-convex frontiers offer more accurate inner approximations of the true technology (Briec *et al.* 2004).

All the above features jointly with novel adaptations are considered in this research work. Although they can be transposed to any sector, the following empirical applications are designed considering the Spanish private and savings banks.

The interest in the Spanish banking sector escalated due to the deregulation process the industry underwent during the end of the 1980s - beginning of the 1990s. This triggered a post-deregulation period known for its enhanced levels of competition and sustainable growth. The industry's reform aimed at improving bank competitiveness while converging with the European banking standards. Banks were required to implement new strategies in accordance with the main deregulation targets such as to: eliminate interest rate controls and investment requirements, relax reserve requirements, remove inter-country barriers to competition, enhance branch expansion and consequently facilitate the entry of foreign and local banks at all levels of the Spanish market. These measures were applied gradually, ending in 1992[1].

Adjustments to the new market structure affected differently the three types of banking institutions existing in the sector: the private banks, the savings banks and the credit cooperatives. These are mainly differentiated by their ownership structure. While the private banks use their private capital to pursue the goal of profit maximization, the savings banks are public companies and the credit cooperatives frequently belong to their customers. Additionally, the private and savings banks control over 95% of the banking assets (see Grifell-Tatjé and Lovell 1997a; Kumbakhar *et al.* 2001; Crespí *et al.* 2004). Due to the differences in market share and organization structure, the technology is homogenous between private and savings banks. Therefore, the following analyses will only consider these two bank types.

[1] One can refer to Kumbakhar *et al.* (2001) or Hasan and Lozano-Vivas (2002) for more extensive views on the deregulation process and its consequences.

The savings banks were the main beneficiaries of the market liberalization. This was primarily due to the removal of interest rates and geographical and procedural restrictions. Thus, the savings banks sought growth and introduced expansion strategies as opening new branches, increasing proximity to customers via the *ATM* networks and conducting *M&As*. Simultaneously, private banks channeled their efforts to meeting the needs of the new competitive market and the policies of the European Union. Their actions included redefining deposits, loans rates and capital standards.

This period of growth and developments reached its peak at the beginning of the 2000s and ended with the recent financial crisis. There are similarities between the consolidation at the beginning of the 1990s and the directions for development stated by the Spanish central bank in 2009. Thus, in view of the upcoming events, it is useful to re-asses through novel perspectives the data available for the post-deregulation period.

Key objectives from the Spanish central bank comprise issues such as providing more safety to bank operations through attaining bigger size and bigger equity, and consequently a better control of operating risks. This viewpoint of the central institution may well be seen as a way of improving bank efficiency by optimizing the networks of branches and clean-ups of toxic assets. Hence, the banking firms will have to take into account their levels of managerial efficiency and establish new competitive and consolidation strategies.

2. Research Objectives, Methods of Achievement and Contribution

In accordance with the stated methodological assumptions, their opportunities for new developments and the Spanish economic context, the next there subsections describe the specific objectives of this dissertation. These are designed to take into account literature gaps as well as associated empirical questions to be addressed via a managerial focus.

2.1. Bank Productivity and Performance Groups

Even though some previous research examined clusters using efficiency analysis (*e.g.* Athanassopoulos 2003; Prior and Surroca 2006) or analyzed the role of bank strategy in shaping the efficient frontier (*e.g.* Bos and Kool 2006), the use of *TFP* measures in these respects is quite novel.

Grounding this first study in the combination between the strategic groups' literature and the efficiency and productivity analysis, the main pursued objectives are to:

Analyze the changes in productivity and efficiency within the Spanish banking sector throughout an eight-year period (1998–2006).

Form and interpret performance groups based on efficiency and productivity indicators.

Following the decomposition of the Malmquist productivity indices suggested by Färe, *et al.* (1994), we propose a novel decomposition of the Luenberger productivity indicator. The disentangled components are efficiency change (further decomposed into pure efficiency change, congestion change, and scale change) and technological change. These show good managerial practices ((pure) efficiency change), innovatory practices (technological change), scale economies progress (scale change) and possible efficiency problems related to input-levels (congestion change).

First, the analysis shows how private and savings banks evolve over time, as well as comparisons among the two bank types and their associated productivity components. Second, the productivity results are used as input variables for a cluster analysis at the entire sector level. In this way, one can identify and interpret the sources of the performance differences observed among bank groups. Moreover, banking ratios offer strategy related interpretations of these performance groups. Therefore, the employed methodology represents an amalgamation of a new technique (Luenberger decomposition) and a traditional one (cluster analysis).

2.2. Technology-Based Total Factor Productivity and Benchmarking

A small existing literature proposes efficiency frontier comparisons using productivity indices combined with some form of unit to unit benchmarking. While consensus is reached concerning the utility of benchmarking, far less agreement exists regarding the choice of benchmarks and method of analysis.

The strategic interest of a firm could be to know its relative performance with respect to a certain specific competitor, instead of comparing itself to an efficiency frontier potentially shaped by various firms in the industry. This competitor may well be the leader of a strategic group, or simply the local competitor irrespective of showing good or bad performance. Also, it is important to scrutinize this positioning in terms of *TFP* and in both static and dynamic contexts. As a function of strategic decision making, efficiency coefficients (static) and *TFP* indices (dynamic) can be equally relevant.

This chapter's specific objective is to:

Propose new TFP benchmarking measures adapted for specific perspectives: (1) static, (2) fixed technology and unit, and (3) dynamic TFP change.

These approaches assume fixed units and/or base technologies as benchmarks, and are defined through different adaptations of Bjurek's (1996) Hicks-Moorsteen index. As before indicated, in contrast to most productivity indices, the standard Hicks-Moorsteen index has a *TFP* interpretation and always leads to feasible results.

A manager can select the most appropriate method for his/her specific benchmark scenario. While each of the three approaches can stand alone, these methods are also potentially complementary. In the latter case, a multidimensional picture can be obtained via the parallel interpretations of these three Hicks-Moorsteen *TFP* indices for benchmarking. An illustration for the Spanish banking sector between 1998 and 2006 serves to illustrate the feasibility and managerial implications of the proposed framework

2.3. Revealing Efficiency Gains from Mergers: Convex vs. Non-Convex Technologies

Consensus exists on the forces driving the banking *M&As*, but the results on efficiency gains remain many times inconclusive (see, *e.g.*, Berger *et al.* 1999; Amel *et al.* 2004). For instance, in the Spanish banking sector, there may be no gains from *M&As* (Grifell-Tatjé and Lovell 1996, 1997b; Lozano-Vivas 1998) or ex post efficiency increases (Cuesta and Orea 2002). One can guess that this situation is partly due to the generally employed convexity assumption.

In practice, convex (*DEA*) estimators indicate larger or equal amounts of inefficiency than the ones of the non-convex methods (*FDH*), which offer more accurate inner approximations of the true technology (Briec *et al.* 2004). Consequently, targeted potential gains established through a convex frontier may be too hard to achieve, as they could be an over-optimistic goal. When revealing gains from *M&As*, these different inefficiency reductions are key for the strategic planning activity and its evaluation.

It may be thus interesting to re-assess some of the previous merger events in view of the upcoming post-crisis *M&As* considering (as suggested by Briec *et al.* (2004)) non-convex technologies and cost functions. Accordingly, the purpose of this chapter is to:

Investigate the cost excess gains from 32 M&As that occurred between 1988 and 2006 in the Spanish banking industry.

Use both convex and non-convex technologies and illustrate the existing differences between the two.

The gains are revealed as reductions of existing cost excess due to scale and technical inefficiencies. These are reported in monetary terms to provide proximity to the managerial community, which mainly analyzes differences instead of ratios. Also, it is hypothesized that cost excess generated through *M&As* represents room for future improvements. Explicitly, the cost excess of the merged bank tends to be superior to the sum of the ex ante cost excesses of the merging banks. Hence, this scenario supports cost reductions that can be attained by means of efficient ex post managerial practices.

This dissertation is structured in three chapters. Chapter 1 is based on the specific objectives in Subsection 2.1 and is titled "Bank Productivity and Performance Groups: A Decomposition Approach Based upon the Luenberger Productivity Indicator". Chapter 2 introduces new proposals of technology-based total factor productivity indices for benchmarking, as indicated in Subsection 2.2. The analysis of efficiency gains from mergers, stated by the objectives in Subsection 2.3, is found in Chapter 3. While each of these chapters can stand alone and be interpreted as such, a final section presents key general conclusions together with links between the studied topics and future research avenues.

Chapter 1:

Bank Productivity and Performance Groups: A Decomposition Approach Based upon the Luenberger Productivity Indicator

Abstract

The purpose of this paper is twofold. First, in the framework of the strategic groups' literature, it analyses changes in productivity and efficiency of Spanish private and savings banks over an eight-year period (1998–2006). Second, by adapting the decomposition of the Malmquist productivity indices suggested by Färe *et al.* (1994), it proposes similar components decomposing the Luenberger productivity indicator. Initially, total factor productivity is decomposed into technological and efficiency changes. Thereafter, this efficiency change is decomposed into pure efficiency, scale and congestion changes. Empirical results demonstrate that productivity improvements are partially due to technological innovation. Furthermore, it is shown how the competition between private and savings banks develops in terms of the analyzed productivity and efficiency components. While private banks enjoy better efficiency change, savings banks contribute more to technological progress. Consequently, the Luenberger components are used as cluster analysis inputs. Thus, economic interpretations of the resulting performance groups are made via key differences in total factor productivity components. Finally, according to the strategic groups' literature, insights are gained by linking these performance groups with banking ratios.

Keywords: Luenberger decomposition, total factor productivity, Spanish banking sector, performance groups, banking ratios.

1. Introduction

The purpose of this paper is to analyze the changes in productivity and efficiency within the Spanish banking sector throughout an eight-year period (1998–2006). Following the decomposition of the Malmquist productivity indices suggested by Färe, *et al.* (1994), we propose a novel decomposition of the Luenberger productivity indicator. Thereafter, we continue by clustering these results to show the significant dissimilarities between performance groups. Thus, the article aims at presenting a comprehensive image of the evolution of the competitive reality of the Spanish banking industry.

The use of primal total factor productivity indices (henceforth *TFP*) in the academic literature on efficiency and productivity has recently experienced an upsurge in popularity. This is because these do not require the availability of prices (information which is not always available), but rather rely on physical inputs and outputs solely. Numerous empirical applications employ the ratio-based Malmquist productivity index (see the survey in Färe *et al.* 1998 or the more recent review in Fethi and Pasiouras 2010). However, fewer applications exist of the Luenberger productivity indicator (Chambers 2002), which determines productivity in terms of differences rather than ratios.

Several differences exist between ratio- and difference-based productivity measures. In index number theory, indicators have been proposed to avoid certain problems with index calculations (see *e.g.*, Diewert 2005). One source of nuisance for the ratio-based indices occurs when the denominator yields a zero value. Of course, these issues are less likely to appear in frontier benchmarking. Nevertheless, Chambers *et al.* (1996) defined Luenberger productivity indicators to answer these issues.[2] Additionally, there is a more practical consideration in favor of the use of indicators. Even if the academic community is familiar with ratios, the business and accounting communities are evidently more accustomed to evaluating cost, revenue, or profit differences in monetary terms (Boussemart *et al.* 2003).

Luenberger indicators are more general than Malmquist indices, since these can be compatible with the goal of profit maximization while the latter normally focus on either cost minimization or revenue maximization (Boussemart *et al.* 2003). Furthermore, Malmquist indices are known to overestimate the productivity change as opposed to the Luenberger indicators (see Boussemart *et al.* 2003; Managi 2003). From a methodological point of view, we decompose the Luenberger productivity indicator in a way similar to the proposal of Färe *et al.* (1994) regarding the Malmquist index into efficiency change (further decomposed into pure efficiency change, congestion change, and scale change) and technological change. These productivity results are used as inputs for a cluster analysis through which we track the origin of the observed differences among bank groups in terms of performance. Moreover, by means of banking ratios we reach economical, strategy related interpretations of these performance groups. Thus, the employed methodology represents an amalgamation of a new technique (Luenberger decomposition) and a traditional one (cluster analysis).

The Spanish banking sector is attractive to analyze because it experienced consistent growth. This growth is situated against the background of the disappearance of regulatory constraints, mainly as a result of the intensive adaptation of the Spanish banking legislation to the European banking rules (Grifell-Tatjé and Lovell 1997b;

[2] As Chambers (2002: 756) states, "one of the most common practical problems with ratio-based indexes is what to do with zero observations, as ratio-based indexes are frequently not well defined in the neighborhood of the origin."

Cuesta and Orea 2002; Zúñiga-Vicente *et al.* 2004). Numerous studies have been looking at the Spanish banks and analyzed their productivity and efficiency from a variety of perspectives (*e.g.* Grifell-Tatjé and Lovell 1996, 1997a, b; Lozano-Vivas 1997; Prior 2003; Tortosa-Ausina 2003, 2004; Crespí *et al.* 2004; Zúñiga-Vicente *et al.* 2004; Más-Ruiz *et al.* 2005; Prior and Surroca 2006; Tortosa-Ausina *et al.* 2008, to name just a few).

Even though some previous research looked at clusters using efficiency analysis (*e.g.* Athanassopoulos 2003 or Prior and Surroca 2006) or analyzed the role of bank strategy in shaping the efficient frontier (*e.g.* Bos and Kool 2006), the use of *TFP* measures in these respects is quite novel. Moreover, the use of the Luenberger productivity indicator in conjunction with the additional cluster analysis is -to the best of our knowledge- non-existent.

This contribution is structured in five sections. Section 2 introduces the Luenberger productivity indicator and its novel decomposition. Section 3 offers a review of the conceptualization of cluster/group division. Sample-related information together with the description of the variables and the methods of analysis are found in Section 4. Section 5 presents the empirical results as well as their interpretation, whereas the final section formulates key conclusions and suggests directions for extending this research.

2. The Luenberger Productivity Indicator and its Decomposition

Based upon the shortage function established by Luenberger (1992a, b), Chambers *et al.* (1996) introduce the Luenberger productivity indicator as a difference of directional distance functions. The advantage of the Luenberger indicator is that, instead of specializing in either input- or output-orientation (as the Shephardian distance function underlying the Malmquist indexes do), it addresses input contractions and output expansions simultaneously and is therefore compatible with the economic goal of profit maximization (Boussemart *et al.* 2003; Managi 2003). According to Chambers (2002: 751) "these Luenberger indicators are novel because they are based on a translation (non radial) representation of the technology and, thus, are all specified in difference (non-ratio) form". Therefore, the Luenberger productivity indicator is a generalization of the Malmquist index (Managi 2003). Additionally, Boussemart *et al.* (2003) establish an approximation result stating that, under constant returns to scale (henceforth *CRS*), the logarithm of the Malmquist index is roughly twice the Luenberger indicator.

Let $\mathbf{x} = (x_1, \ldots, x_N) \in R_+^N$ and $\mathbf{y} = (y_1, \ldots, y_M) \in R_+^M$ be the vectors of inputs and outputs, respectively, and define the technology by the set T^t, which represents the set of all output vectors (**y**) that can be produced using the input vector (**x**) in the time period t:

$$T^t = \left\{ \left(\mathbf{x^t}, \mathbf{y^t} \right) : \mathbf{x^t} \text{ can produce } \mathbf{y^t} \right\}. \quad (1)$$

Following Briec (1997: 105), the proportional distance function is defined as:

$$D^t \left(\mathbf{x^t}, \mathbf{y^t} \right) = \max \left\{ \delta : ((1 - \delta)\mathbf{x^t}, (1 + \delta)\mathbf{y^t}) \in T^\mathbf{t} \right\}. \quad (2)$$

This distance function completely characterizes technology at period t.

The Luenberger indicator, specified by Chambers *et al.* (1996) and Chambers (2002), is now given by:

$$\begin{aligned} L^{t,t+1} \left(\mathbf{x^t}, \mathbf{y^t}, \mathbf{x^{t+1}}, \mathbf{y^{t+1}} \right) = \frac{1}{2} \Big[& \left(D^t \left(\mathbf{x^t}, \mathbf{y^t} \right) - D^t \left(\mathbf{x^{t+1}}, \mathbf{y^{t+1}} \right) \right) \\ & + \left(D^{t+1} \left(\mathbf{x^t}, \mathbf{y^t} \right) - D^{t+1} \left(\mathbf{x^{t+1}}, \mathbf{y^{t+1}} \right) \right) \Big]. \end{aligned} \quad (3)$$

This formulation represents an arithmetic mean between the period t (the first difference) and the period $t+1$ (the second difference) Luenberger indicators, whereby each Luenberger indicator consists of a difference between proportional distance functions evaluating observations in period t and $t+1$ with respect to a technology in period t respectively period $t+1$. Hence, the arithmetic mean, Chambers *et al.* (1996), avoids an arbitrary selection among base years.

The above definition can be decomposed into two components:

$$
\begin{aligned}
L^{t,t+1}\left(\mathbf{x}^{t},\mathbf{y}^{t},\mathbf{x}^{t+1},\mathbf{y}^{t+1}\right) &= EC^{t,t+1}+TC^{t,t+1} = \\
&= \left(D^{t}\left(\mathbf{x}^{t},\mathbf{y}^{t}\right)-D^{t+1}\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1}\right)\right)+ \\
&+\frac{1}{2}\left[\left(D^{t+1}\left(\mathbf{x}^{t},\mathbf{y}^{t}\right)-D^{t}\left(\mathbf{x}^{t},\mathbf{y}^{t}\right)\right)+\left(D^{t+1}\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1}\right)-D^{t}\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1}\right)\right)\right],
\end{aligned}
\tag{4}
$$

where the first difference expresses the efficiency change between periods t and $t+1$ (henceforth *EC*) and the arithmetic mean of the two last differences represents the technological change between periods t and $t+1$ (henceforth *TC*). *EC* measures the evolution of the relative position of a given observation with respect to a changing production frontier. The *TC* component provides a local measure of the change in the production frontier itself measured with respect to a given observation in both periods. This represents technological progress or regress, depending on the positive or negative sign.

This decomposition is similar to the basic one known for the Malmquist index (first introduced in Färe *et al.* 1989, 1992). It has been empirically applied to the Luenberger indicator by several authors (*e.g.* Managi 2003; Mussard and Peypoch 2006; Barros *et al.* 2008; Williams *et al.* 2009). Consequently, we propose a decomposition of the Luenberger indicator similar to the one applied to the Malmquist index by Färe *et al.* (1994: 227-235). The basis for this specification is the above formulation. While the technological change component remains unaffected, the efficiency change component is further decomposed into pure efficiency change (henceforth *PEC*), scale efficiency change (henceforth *SC*) and congestion change (henceforth *CGC*).

Furthermore, while equations (3) and (4) are defined with respect to technologies imposing *CRS* and strong disposability of inputs and outputs (henceforth *SD*), these new components require other specifications of technology. Apart from the above, this decomposition requires employing technologies satisfying variable returns to scale (henceforth *VRS*) and assumptions of weak disposability of inputs (henceforth *WD*), while maintaining the strong disposability assumption for the outputs.

To be more precise, the efficiency change component (*EC*) can be decomposed as follows:

$$\begin{aligned} EC^{t,t+1}\left(\mathbf{x}^{t},\mathbf{y}^{t},\mathbf{x}^{t+1},\mathbf{y}^{t+1}\right) = {} & PEC^{t,t+1}\left(\mathbf{x}^{t},\mathbf{y}^{t},\mathbf{x}^{t+1},\mathbf{y}^{t+1}\right) + SC^{t,t+1}\left(\mathbf{x}^{t},\mathbf{y}^{t},\mathbf{x}^{t+1},\mathbf{y}^{t+1}\right) + \\ & + CGC^{t,t+1}\left(\mathbf{x}^{t},\mathbf{y}^{t},\mathbf{x}^{t+1},\mathbf{y}^{t+1}\right), \end{aligned} \tag{5}$$

where

$$PEC^{t,t+1}\left(\mathbf{x}^{t},\mathbf{y}^{t},\mathbf{x}^{t+1},\mathbf{y}^{t+1}\right) = D^{t}\left(\mathbf{x}^{t},\mathbf{y}^{t} \mid VRS,WD\right) - D^{t+1}\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1} \mid VRS,WD\right), \tag{6}$$

$$\begin{aligned} SC^{t,t+1}\left(\mathbf{x}^{t},\mathbf{y}^{t},\mathbf{x}^{t+1},\mathbf{y}^{t+1}\right) = {} & \left[D^{t}\left(\mathbf{x}^{t},\mathbf{y}^{t} \mid CRS,SD\right) - D^{t}\left(\mathbf{x}^{t},\mathbf{y}^{t} \mid VRS,SD\right)\right] + \\ & + \left[D^{t+1}\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1} \mid VRS,SD\right) - D^{t+1}\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1} \mid CRS,SD\right)\right], \end{aligned} \tag{7}$$

$$\begin{aligned} CGC^{t,t+1}\left(\mathbf{x}^{t},\mathbf{y}^{t},\mathbf{x}^{t+1},\mathbf{y}^{t+1}\right) = {} & \left[D^{t}\left(\mathbf{x}^{t},\mathbf{y}^{t} \mid VRS,SD\right) - D^{t}\left(\mathbf{x}^{t},\mathbf{y}^{t} \mid VRS,WD\right)\right] + \\ & + \left[D^{t+1}\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1} \mid VRS,WD\right) - D^{t+1}\left(\mathbf{x}^{t+1},\mathbf{y}^{t+1} \mid VRS,SD\right)\right]. \end{aligned} \tag{8}$$

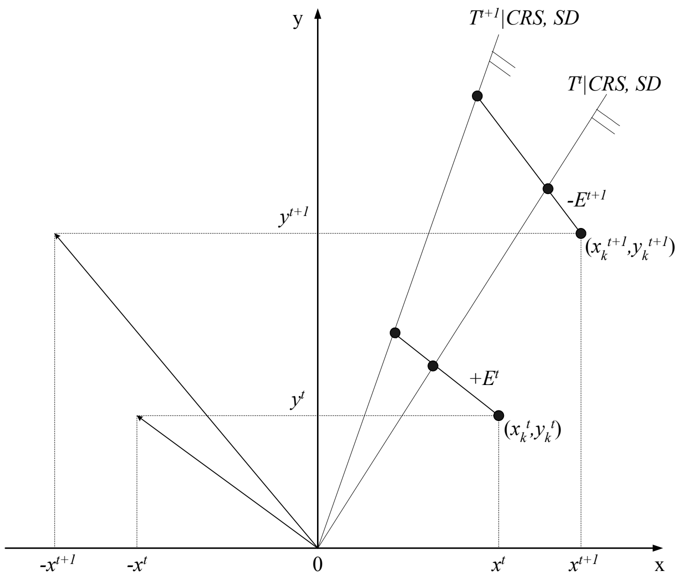
where, *VRS* | *SD* and *VRS* | *WD* stand for variable returns to scale and strong respectively weak disposability. Similarly, *CRS* | *SD* represents constant returns to scale and strong disposability. Therefore, the components of the entire decomposition are: *TC* and *EC*, and the latter is broken down into *PEC*, *SC* and *CGC*.[3]

Figure 1.1, assuming a simple technology with only one output and one input, illustrates the basic components *EC* and *TC*. On the one hand, *TC* can be observed

[3] This formulation follows the Malmquist decomposition in Färe *et al.* (2004: 235). However, it should be noted that the decompositions (7) and (8) depend on the order in which they are done (see Färe and Grosskopf (2000) for more details).

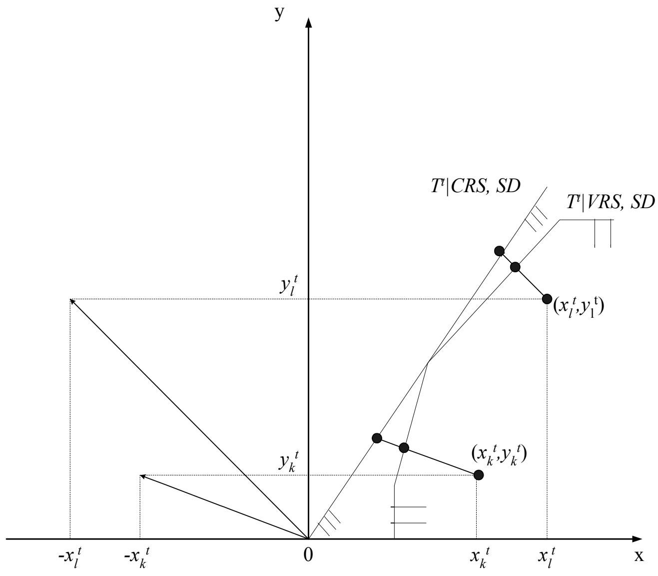
graphically and, as represented in equation (4), it embodies the shift of the frontier between the two periods t and $t+1$ ($TC^{t,t+1}$). On the other hand, the EC is given by the distance from where the unit (k) is situated in period t ((x_k^t, y_k^t) in the figure) to the frontier in t (E^t in Figure 1.1), minus the distance from the unit in $t+1$ ((x_k^{t+1}, y_k^{t+1}) in the figure) to the frontier in $t+1$ (E^{t+1} in Figure 1.1).

Figure 1.1. Efficiency Change and Technological Change



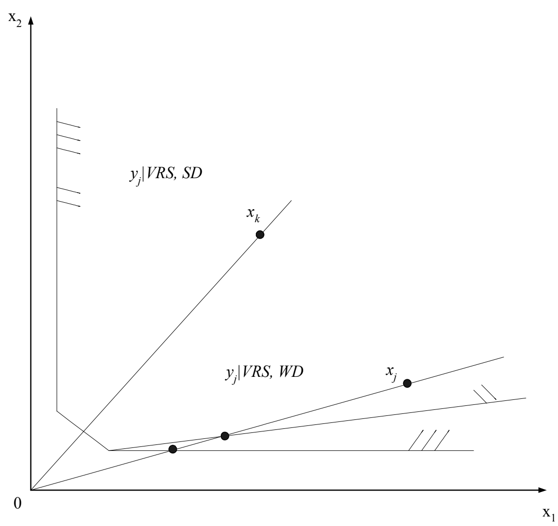
As observed in equation (7), the SC represents the movements in scale inefficiencies between two periods. These scale inefficiencies are given by the difference among the CRS and VRS frontiers. Let us take one arbitrary period (t) as an example together with two units (k and l) (see Figure 1.2). Both (x_k^t, y_k^t) and (x_l^t, y_l^t) show input scale inefficiencies. In the case of unit (x_k^t, y_k^t) the source is the production of an inefficiently small output in the presence of increasing returns to scale. Correspondingly, unit (x_l^t, y_l^t) produces an inefficiently large output while decreasing returns to scale are present.

Figure 1.2. Scale Inefficiency (adapted from Färe et al. 1994: 75)



Finally, "the input congestion measure provides a comparison of the feasible proportionate reduction in inputs required to maintain output when technology satisfies weak versus strong input disposability" (Färe *et al.* 1994: 75). Figure 1.3, assuming a technology with two inputs needed to produce one output, shows that the input mix corresponding to vector x_j is congested due to input 1, as the inefficiency in *SD* is greater than in *WD*. Consequently, input vector x_k is not congested since the inefficiency in *SD* is equal to the one in *WD*.

Figure 1.3. Input Congestion (Färe et al. 1994: 76)



Notice that all of the above productivity changes are interpreted following the logic inherent to difference-based indicators. Productivity improvements are denoted by positive numbers in any of the components. Likewise, negative values represent some productivity decline (technological regress in the case of *TC*) from period *t* to period *t+1*.

3. Strategic/Performance Groups

The clustering of firms within an industry is closely linked with the notion of strategic groups. This concept, initially proposed by Hunt (1972), aims at identifying similar configurations of firms' behavior within a given industry. Porter (1979) conceives a strategic group as a collection of firms that share similar strategic options within the same sector. Furthermore, Caves and Porter (1977) and Porter (1980) state that the construction of such a group depends on whether firms respond to the competitor's initiatives in a systematically similar way.

Moreover, while initially attention was given to industry-specific characteristics, Fiegenbaum and Thomas (1994) advanced research by taking a firm-specific focus. Hence, a cluster is delimited by "a set of firms competing within an industry on the basis of similar combinations of scope and resource commitments" (Cool and Schendel 1987: 1106). This approach towards grouping firms is still being utilized (*e.g.* Prior and Surroca (2006) for a study in the banking industry).

While the extant literature is somewhat successful when dealing with the issue of grouping analyzed units, other important aspects such as the connection between a cluster and its level of performance are often neglected, or related empirical results are simply not convincing (Thomas and Venkatraman 1988; Barney and Hoskisson 1990).

However, it must be mentioned that recently efforts were made to remedy these specific problems (*e.g.* Mehra 1996; Athanassopoulos 2003; Short *et al.* 2007).

Prior and Surroca (2006) formulate two possible causes for this situation: (1) the correlation among group membership and performance has not been expressed properly, or (2) strategic groups are just an analytical construct (Hatten and Hatten 1987) and such links simply do not exist. Also reflecting upon this situation, Day *et al.* (1995) state that conflicting results on performance differences between groups may appear due to the lack of the use of multiple criteria and the employment of inappropriate selection methods.

Additionally, Day *et al.* (1994, 1995) speculate that one of the main problems is that firms pursue multiple goals, whereas cluster analysis cannot handle such multidimensional problems. Nevertheless, even though Ketchen and Shook (1996: 455) agree about problems with its past use, they state that cluster analysis provides a “valuable” and “important tool” for discerning groups of firms. In addition, this method allows for both deductive (*i.e.* a priori expectations about the clusters’ existence) as well as inductive (*e.g.* there are no such prior expectations) methods of investigation, thus permitting the use of diverse theoretical frameworks.

In recent literature, cluster analysis techniques have also been developed in conjunction with efficiency analysis. Po *et al.* (2009) present a clustering method linked with non-parametric frontier methods (also known as Data Envelopment Analysis (*DEA*)), which allows for each unit to know its corresponding cluster. Also using *DEA*, Sohn (2006) states that efficiency results can be employed to group units. In this case, membership could be attributed to the environmental characteristics of each firm. In the banking industry, Ray and Das (2010) estimate cost and profit efficiencies and subsequently compare banks with similar activity through ratio-based cluster analysis.

From this discussion, we draw two conclusions. First, it would be highly desirable that the outcome of the cluster analysis can be studied such that productivity differences among groups are clearly revealed. Second, the clustering technique needs to fit well within the research methodology.

Clusters are generally formed based on variables that explain certain distinct behaviors. As proposed by Amel and Rhoades (1988) for banking strategies, each group is characterized by a key variable (*i.e.* a performance ratio) which distinguishes it from others. A classical approach is that of Zúñiga-Vicente *et al.* (2004) (a study of Spanish banking) and/or Ray and Das (2010) (an evaluation of Indian banking) that use banking performance indicators as inputs for the cluster analysis. Moreover, Ray and Das (2010) cluster banks with similar activities subsequent to the interpretation of efficiency coefficients. Alternative variables are found in Prior and Surroca (2006) where banking units are clustered by means of marginal rates and are further analyzed through conventional efficiency techniques.

Taking into account our stated aim to look at the productivity of the sector we select the Luenberger decomposition results as cluster analysis variables. This issue is presented in greater detail in the following section.

4. Data, Variables and Method of Analysis

4.1. Description of the Sample

As stated before, the competitive pressure in the Spanish banking increased due to the gradual disappearance of regulatory constraints that began in the late 1980s (Grifell-Tatjé and Lovell 1997b; Cuesta and Orea 2002; Zúñiga-Vicente *et al.* 2004). Consequently, year 1989 is the threshold to the liberalized market, as emergent financial intermediaries were allowed to carry out activities normally linked with private banks

(Zúñiga-Vicente *et al.* 2004). The savings banks have been the main beneficiaries of the deregulation process. Not only that they have been allowed to perform general banking operations, but they could also expand throughout all Spanish provinces.

A next important step is taken in 1995 as a new legal regime for the creation of banks appears. The sector integrates intensively new technologies and financial products and services (Cuesta and Orea 2002; Zúñiga-Vicente *et al.* 2004). This technological revolution, together with the end of the economic crisis that occurred between the years 1992 and 1996, makes way for enhanced competition. Thus, the years 1997-1998 stand for the beginning of a strong economic growth in the Spanish economy. Moreover, studying annual reports of private and savings banks allows one to infer that, at the turn of the century, expansion is one of the main priorities.

There are three types of banking institutions: private banks, savings banks and credit cooperatives. The main difference between the three types is given by the ownership structure. On the one hand, private banks are classical profit-seeking firms. On the other hand, the savings banks have a public status, and credit cooperatives are most often held by customers. Additionally, the market is dominated by the private and savings banks, leaving to the credit cooperatives only about 2% of the banking activity (Grifell-Tatjé and Lovell 1997a). Also, while technology is homogeneous for private and savings banks, credit cooperatives, largely due to their reduced size, are less developed from this point of view. Hence, apart from having few branches, they also have a small amount of *ATMs* and financial products and services. Accordingly, their operations are conducted by means of lower levels of information technology.

Consequently, the year 1998 represents the end of both the deregulation period and the financial crisis. It marks the beginning of a new growth period and novel corporate strategies, especially in the case of savings banks. Considering this together with the fact that private and savings banks operate using similar technologies, the sample is formed of these two bank types starting with the year 1998. The only discarded units were foreign private banks which did not have reliable asset-related information. Furthermore, literature states that strategic plans are set up "in terms of performance goals, approaches to achieving these goals, and planned resource commitments over a specific time period, typically three to five years" (Grant 2008: 21). Thus, having information available until year 2006, we defined two time periods to study: 1998-2002 and 2002-2006. Having two periods, each with several years, allows seeing clearer the eventual changes in the *TFP* indicators between these analyzed periods.

First, we tested for the eventual presence of outliers. It is common knowledge that outliers, as extreme points, may well determine the non-parametric production frontier used in the computation of the Luenberger indicator and can create bias in the efficiency and productivity change estimated in any given sample. Andersen and Petersen's (1993) super-efficiency measure together with Wilson's (1993) study are the seminal works on outliers in a frontier context. Consequently, when possibly influential units are encountered, these are often removed from the sample and the super-efficiency measures are recalculated and compared with the previous ones. Furthermore, as suggested by Prior and Surroca (2006), this process is repeated until the null hypothesis of equality between successive efficiency scores cannot be rejected. Using this method, it is found that approximately 6% of the units in the sample were potential outliers.

Next, two redefined samples are formed. By matching the existing units through the 1998-2002 and 2002-2006 intervals, the samples contain 96 banking units in the first time-period and 93 in the second one. While each of them is a balanced panel, they are slightly different between each other. This is due to the presence of different outliers between periods, or the appearance and disappearance of certain banking units.

4.2. Input and Output Variables and Method of Analysis

Banking activity can be defined through different methods (see the surveys of Berger and Humphrey (1997) or Goddard *et al.* (2001) for more details). At first glance, the situation seems a bit chaotic due to the diversity between approaches. Nonetheless, the reviewed research evaluates dissimilar dimensions of banking efficiency. As pointed out by Berger and Humphrey (1997: 197), “there are two main approaches to the choice of how to measure the flow of services provided by financial institutions”. These are the production and the intermediation approaches. On the one hand, under the production approach banks are generally considered producers of deposit accounts and loan services. Also, within this specification, only physical inputs such as labor and capital and their costs are to be included. On the other hand, the intermediation approach views banks as mediators that turn deposits and purchased funds into loans and financial investments (Favero and Papi 1995). Therefore, in this case, funds and their interest cost (which are the raw material to be transformed) should be present as inputs in the analysis (Berger and Humphrey 1997).

The present study opts to take deposits as an output, and hence chooses a traditional production approach. The reasoning behind this choice is the output characteristics of deposits associated with liquidity, safekeeping and, payment services provided to depositors (Berger and Humphrey 1997). Inputs are (1) operative assets (defined as total assets – financial assets), (2) labor (number of employees), and (3) other administrative expenses. Outputs are (1) deposits, (2) loans, and (3) fee-generated income (non-traditional output). The variables are with one exception (labor) in monetary terms. First, the rationale for this specification is relatively simple. For example, let us consider two banks that have the same number of deposits, but one of them holds twice the value of the other in monetary terms. The physical deposits would be equal, whereas the monetary deposits would show the real situation. Second, labor is expressed in absolute numbers as the values showed higher consistency throughout the sample, thus producing less bias.

Accordingly, using this production approach the analysis is developed throughout two stages: (1) the Luenberger decomposition, and (2) the cluster analysis and the associated significance tests. First, the Luenberger decomposition is computed in accordance with the formulation presented in Section 2.

At this point a further explanation is necessary. With the exception of congestion, all the decomposition components are calculated with respect to all inputs and outputs. However, as the weak disposability assumption (see Färe *et al.* 1994) can represent an extreme form of efficiency in any specific input or output, a different specification was preferred. By reviewing our definition of the output mix, all outputs are clearly desirable, meaning that the weak disposability assumption is not applicable for the output side. However, the situation on the input side is rather different. Despite the fact that according to the declared expansion plans one expects all inputs to increase, there still remains the problem of controlling their optimal quantity and mix to avoid ending up with input congestion (whereby adding an input leads to less outputs). With expansion as the strategic background, the labor input should be cautiously treated. More employees than needed can cause the appearance of operations with no value added or high levels of bureaucracy and/or sterile controls. All these generally emerge as a way of justifying the excessive number of employees. Therefore, congestion is measured to account for the possible negative impact of the labor input on outputs.

The Luenberger indicator shows the changes between 1998-2002 and 2002-2006. At this point, an intermediary interpretation is carried out both at the level of the whole sample, as well as for its two components (*i.e.* private banks and savings banks). Also, results are reviewed and possible infeasible solutions are reported thus leading to sample redefinition. Consequently, two cluster divisions are attained corresponding to the two samples. The input variables for the cluster analysis are the results of the Luenberger decomposition (see Section 2). The correct number of groups together with their composition is given by a hierarchical cluster analysis. Furthermore, the accuracy of the distribution is tested by means of a discriminant analysis.

Subsequently, the interpretation of the results is done by looking upon the significant differences between the groups (following Amel and Rhoades (1988), each group is characterized by certain variables). While the performance groups are based on the Luenberger components, their interpretation is also carried out through performance ratios practitioners use when referring to the banking industry.

Throughout the paper, the differences are tested by means of the Li test (see Li 1996; Kumar and Russell 2002; Simar and Zelenyuk 2006). This is a non-parametric test statistic for comparing two unknown distributions making use of kernel densities. Moreover, as Kumar and Russell (2002: 546) state, “Qi Li (1996) has established that this test statistic is valid for dependent as well as independent variables”. As opposed to most statistical significance tests (*e.g.* Mann-Whitney, Kolmogorov-Smirnov, Wilcoxon), this is not a mean or median level test, as it compares the whole distributions against each other. Consequently, through the p-value of the Li test one can accept or reject the null hypothesis of equality of distributions between the samples.

5. Empirical Results

5.1. Productivity and Efficiency of Private and Savings Banks

The first step of the analysis provides the productivity decomposition scores for the two samples. Table 1.1 and Figure 1.4 present the associated descriptive statistics. It should be mentioned that the entire analyzed samples are maintained as no infeasibilities appeared. With respect to the years under study, the Spanish banking sector is showing, up to a certain extent, the expected results. In terms of productivity the total Luenberger indicator (*L*) scores point to general improvements. Both four-year periods show improvements in the productivity and efficiency indicators, with higher values in the second period. This can be observed in Figure 1.4 through the roughly 2-to-1 ratio between the two time periods for the mean values of the Luenberger measure (*L*) and the technological change (*TC*). First, this seems to represent a continuation of the good use of resources in the Spanish banking industry, and the increase in competition manifested throughout the post-deregulation phase. Second, new information technologies and innovative practices form the basis of the positive shifts of the frontier (see *TC* results of 0.24 in 2002-2006 and of 0.10 in 1998-2002).

Figure 1.4. Luenberger Decomposition: Sample Mean Values

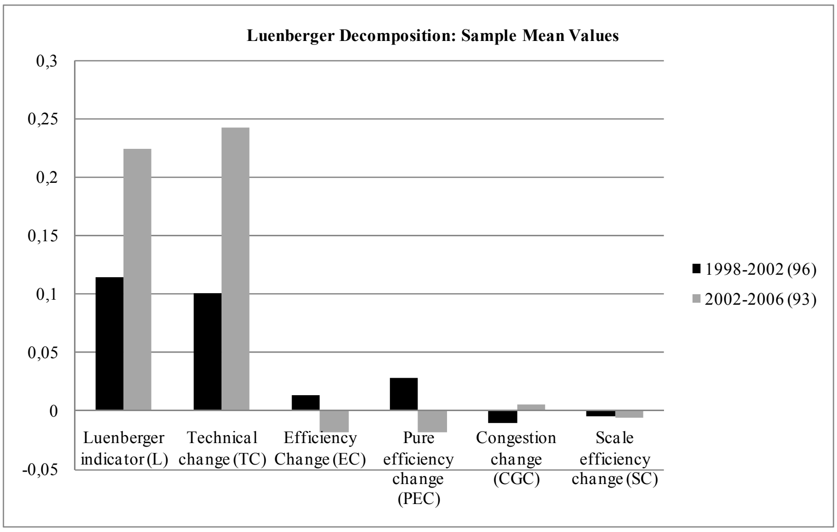


Table 1.1. Luenberger Decomposition: Total Sample Results

1998 – 2002		Mean	Std. dev.	Min.	Max.
Total (96 units)	L	0.1138	0.1339	-0.3480	0.7031
	TC	0.1002	0.0624	-0.1395	0.2913
	EC	0.0136	0.1131	-0.3503	0.5090
	PEC	0.0282	0.0988	-0.2546	0.5026
	CGC	-0.0103	0.0359	-0.1440	0.1204
	SC	-0.0042	0.0582	-0.2954	0.1945
2002 – 2006		**Mean**	**Std. dev.**	**Min.**	**Max.**
Total (93 units)	L	0.2239	0.1435	-0.1632	0.8826
	TC	0.2419	0.0379	0.1492	0.4176
	EC	-0.0180	0.1401	-0.3581	0.6859
	PEC	-0.0179	0.1141	-0.4333	0.5300
	CGC	0.0053	0.0273	-0.0761	0.1212
	SC	-0.0054	0.1123	-0.5429	0.7655

However, through the decomposed factors we can identify that the two periods are not necessarily similar. Even if the Luenberger indicator (*L*) and the technological component (*TC*) are quite higher in the second period, this is not so for the rest of the components. At a first glance, Figure 1.4 illustrates the sign differences for efficiency change (*EC*), pure efficiency change (*PEC*) and congestion change (*CGC*). The efficiency change (*EC*) decreased from 0.0136 to -0.018 hinting that albeit 2002 was better than 1998 in terms of efficiency, this rising trend did not continue to 2006. In the utilized decomposition, this is the sum of pure efficiency change (*PEC*), congestion change (*CGC*) and scale efficiency change (*SC*).

On the one hand, the positive efficiency change (*EC*) in 2002 with respect to 1998 was the effect of successful managerial practices (see also the pure efficiency measure (*PEC*)). On the other hand, in 2006 with 2002 as a benchmark, the pure efficiency change (*PEC*) and the scale efficiency change (*SC*) have negative values (although not very alarming as they maintain themselves in the vicinity of the zero value). Thus, it is possible that the expansion offered a good start-up, while problems with the use of inputs and outputs appeared in the second period. Conversely, the congestion change (*CGC*) results are better in the second period. This outcome is interesting in the background of the expansion process. Nonetheless, these changes are quite close to the zero value, hence the congestion issue remains apparently non-problematic.

5.2. Relation between Private and Savings Banks According to the Luenberger Indicators

Table 1.2 and Figures 1.5 to 1.8 present results according to the type of banking unit. These are similar to the ones related to the total sample. Moreover, they are in the spirit of the global competition, as some components are showing better results for private banks and others for savings banks. Using Table 1.2 and Figure 1.5, one can note that in the first period savings banks perform significantly better with respect to the Luenberger indicator (*L*), the technological change (*TC*) and the pure efficiency change (*PEC*). Nevertheless, we observe that private banks have better efficiency change (*EC*) and no scale efficiency change (*SC*) problems. Thus, a speculation is that in 1998-2002 the savings banks introduced more innovative practices and new technologies, as captured by the technology change indicator (*TC*).

Figure 1.5. Luenberger Decomposition for 1998-2002: Mean Values by Bank Type

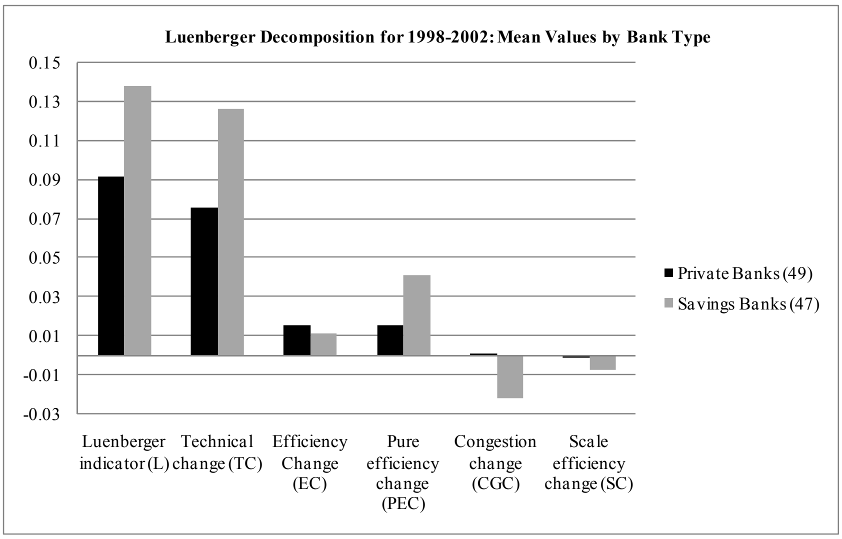


Figure 1.6. Luenberger Decomposition for 2002-2006: Mean Values by Bank Type

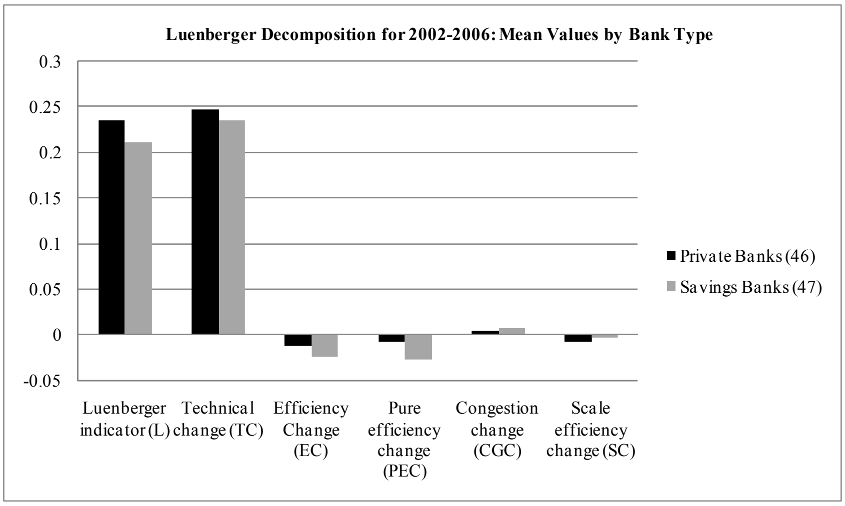


Table 1.2. Luenberger Decomposition: Results per Bank-Type

1998 – 2002		Mean	Std. Dev.	Min.	Max.	Li Test (t-stat./p-value)
L	**PB (49)**	0.0913	0.1787	-0.3480	0.7031	3.5280
	SB (47)	0.1373	0.0510	0.0266	0.2561	0.0002*
TC	**PB (49)**	0.0758	0.0763	-0.1395	0.2913	11.5185
	SB (47)	0.1256	0.0260	0.0066	0.1634	0.0000*
EC	**PB (49)**	0.0155	0.1490	-0.3503	0.5090	1.7182
	SB (47)	0.0117	0.0570	-0.0987	0.2494	0.0428*
PEC	**PB (49)**	0.0157	0.1293	-0.2546	0.5026	3.1393
	SB (47)	0.0412	0.0489	-0.0759	0.1478	0.0008*
CGC	**PB (49)**	0.0008	0.0320	-0.1440	0.1204	0.0754
	SB (47)	-0.0220	0.0363	-0.1329	0.0034	0.4699
SC	**PB (49)**	-0.0011	0.0714	-0.2954	0.1534	3.0761
	SB (47)	-0.0074	0.0407	-0.0957	0.1945	0.0010*
2002 – 2006		**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Li Test (t-stat./p-value)**
L	**PB (46)**	0.2360	0.1938	-0.1632	0.8826	1.1228
	SB (47)	0.2120	0.0645	0.0401	0.3234	0.1307
TC	**PB (46)**	0.2481	0.0478	0.1492	0.4176	1.7875
	SB (47)	0.2358	0.0237	0.1725	0.2986	0.0369*
EC	**PB (46)**	-0.0121	0.1900	-0.3581	0.6859	1.3167
	SB (47)	-0.0238	0.0624	-0.2040	0.0762	0.0939*
PEC	**PB (46)**	-0.0078	0.1446	-0.4333	0.5300	3.0927
	SB (47)	-0.0279	0.0734	-0.2524	0.1686	0.0009*
CGC	**PB (46)**	0.0034	0.0227	-0.0406	0.1212	1.3968
	SB (47)	0.0073	0.0312	-0.0761	0.0843	0.0812*
SC	**PB (46)**	-0.0077	0.1558	-0.5429	0.7655	0.0031
	SB (47)	-0.0032	0.0382	-0.1277	0.0709	0.4987

The values between parentheses represent the number of units for each of the two bank types.
*: Statistically significant differences

The global competition assumption is even clearer in the second period, as the Luenberger measure (*L*) distributions show no significant difference between the two bank types. Besides, the technological change (*TC*) mean values are roughly equal, although there are differences in the distribution of the results. Comparisons are shown in Table 1.2 and Figure 1.6. One can highlight the efficiency change (*EC*) difference in favor of the private banks. This better efficiency change (*EC*) of private banks is consistent with the first period, even though negative changes are attained. In addition, all outcomes are in accordance with the interpretations in Subsection 5.1.

Figure 1.7. Luenberger Decomposition for Private Banks: Mean Values by Period

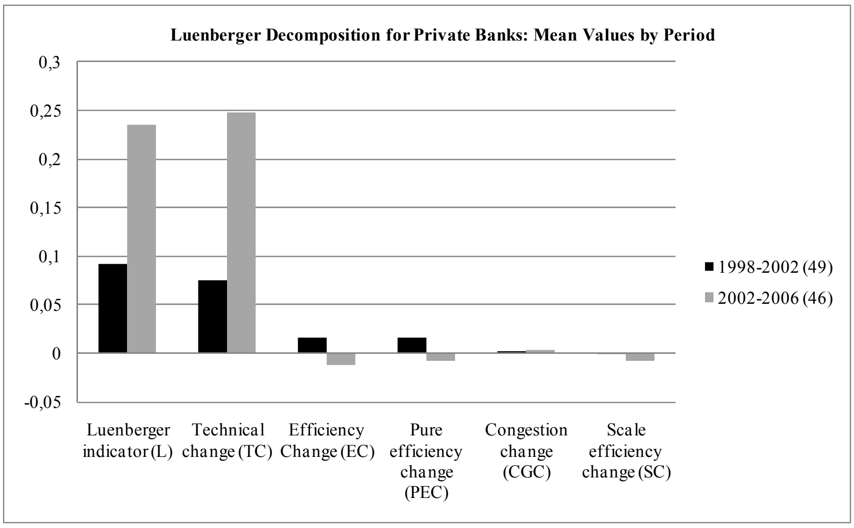
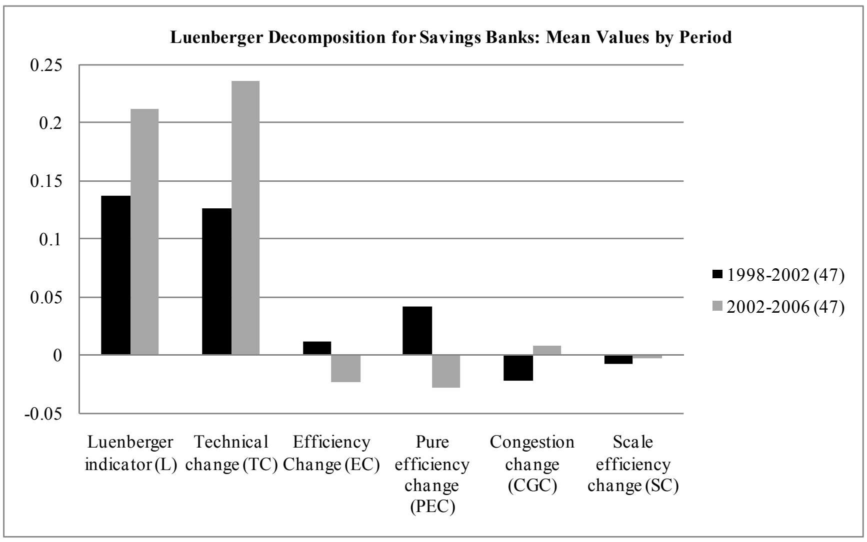


Figure 1.8. **Luenberger Decomposition for Savings Banks: Mean Values by Period**



Further insights can be achieved comparing the private and savings banks between the two periods (see Figures 1.7 and 1.8). These figures indicate that the 2-to-1 ratio between the two periods for the Luenberger measure (*L*) and the technological change (*TC*) (see Subsection 5.1.) is mostly generated by the private banks. In their case this ratio is even larger than 2-to-1, with respect to both the Luenberger (*L*) and technological change (*TC*) indicators. At the same time, for the savings banks the same ratios are quite smaller, showing values of 1.54 for the Luenberger indicator (*L*) and 1.88 in the case of the technological change (*TC*). Furthermore, one can also notice the inefficient employment of inputs and outputs in the case of the savings banks. This is shown mainly by the negative evolution of the pure efficiency change (*PEC*) component. However, at the same time a positive improvement of savings banks is found in the congestion change (*CGC*) indicator.

One can hypothesize that the labor input was congested during the expansion process at the end of the 1990s and that, subsequently, the situation improved. Congestion increased (see negative *CGC* in Table 1.2 and Figure 1.8) when the savings banks shifted from a static market position to a growth phase involving an expansion of their number of branches. However, once the expansion had been realized, the savings banks directed their efforts to solving the congestion problem. Therefore, the congestion change component (*CGC*) shows a positive value. For the private banks no important movements are found in terms of the congestion (*CGC*) and scale efficiency (*SC*) changes, both of which have values close to zero.

5.3. Performance Groups and Their Economic Interpretations

The above outcomes provide the basis for the second stage of the analysis. The clustering results for the Luenberger decomposition are shown in Table 1.3 and Figure 1.9 (descriptive statistics) and Table 1.4 (Li test significance differences). For both

1998-2002 and 2002-2006 periods, the indicated number of performance groups is three. The discriminant analysis confirms that the groups are correctly formed, since the predictions yield more than 90% accurate classifications. Furthermore, the clusters are not separated as a function of bank-type, but as a result of productivity scores. By evaluating the two periods' clustering outcomes, one can notice important changes in the groups' structure. Hence, the hypothesis of stability between the two analyzed intervals is rejected. These changes should be looked at from the point of view of strategic planning. As mentioned before, strategic options are generally revised after three to five years (Grant 2008). Logically, the Luenberger indicator components change through time and lead to dissimilar group composition among the two studied periods (*i.e.* 1998-2002 and 2002-2006). Consequently, from this point onward, the two obtained divisions will be treated as independent.

Figure 1.9. Luenberger Decomposition: Mean Values at Group Level

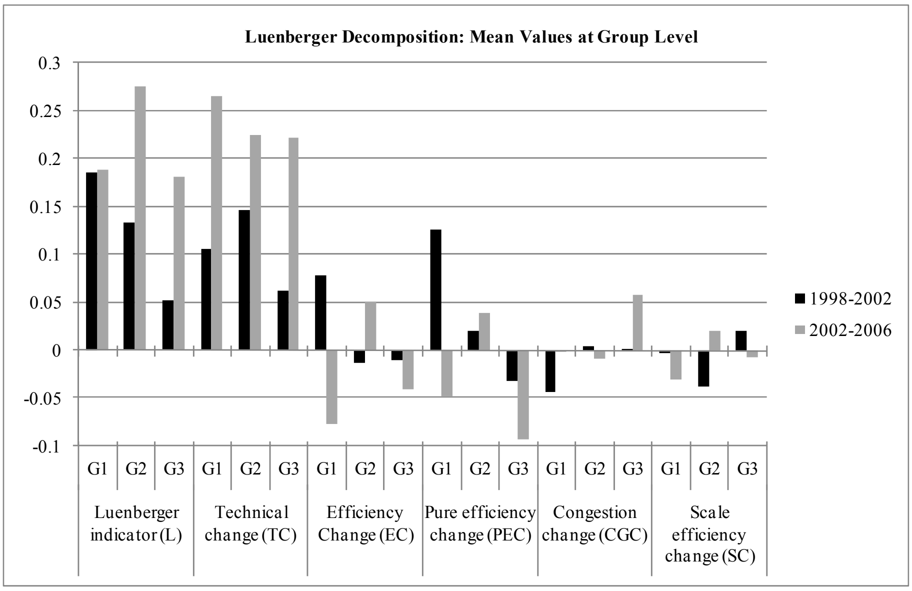


Table 1.3. Luenberger Decomposition: Group Level Descriptive Statistics

1998-2002		Mean	Std. Dev	Min.	Max.
L	**G1 (27)**	0.1849	0.1443	-0.0625	0.7032
	G2 (29)	0.1331	0.1003	-0.1753	0.4173
	G3 (40)	0.0520	0.1219	-0.3481	0.2562
TC	**G1 (27)**	0.1060	0.0604	-0.1396	0.1941
	G2 (29)	0.1467	0.0409	0.0903	0.2913
	G3 (40)	0.0625	0.0528	-0.0837	0.1521
EC	**G1 (27)**	0.0789	0.1346	-0.1412	0.5091
	G2 (29)	-0.0136	0.0811	-0.2954	0.1259
	G3 (40)	-0.0106	0.1016	-0.3504	0.2495
PEC	**G1 (27)**	0.1263	0.1032	0.0000	0.5027
	G2 (29)	0.0207	0.0338	-0.0564	0.0943
	G3 (40)	-0.0324	0.0736	-0.2547	0.0562
CGC	**G1 (27)**	-0.0440	0.0458	-0.1441	0.0235
	G2 (29)	0.0040	0.0224	-0.0053	0.1204
	G3 (40)	0.0019	0.0171	-0.0254	0.0616
SC	**G1 (27)**	-0.0034	0.0362	-0.0868	0.1295
	G2 (29)	-0.0383	0.0624	-0.2954	0.0102
	G3 (40)	0.0199	0.0560	-0.0957	0.1945
2002-2006		**Mean**	**Std. Dev**	**Min.**	**Max.**
L	**G1 (40)**	0.1881	0.1267	-0.1632	0.4177
	G2 (39)	0.2760	0.1625	0.1001	0.8827
	G3 (14)	0.1813	0.0806	0.0384	0.2839
TC	**G1 (40)**	0.2656	0.0426	0.1492	0.4177
	G2 (39)	0.2248	0.0230	0.1661	0.2855
	G3 (14)	0.2221	0.0137	0.2078	0.2429
EC	**G1 (40)**	-0.0775	0.1048	-0.3581	0.1205
	G2 (39)	0.0512	0.1588	-0.0871	0.6859
	G3 (14)	-0.0408	0.0813	-0.1746	0.0710
PEC	**G1 (40)**	-0.0479	0.1015	-0.4334	0.2305
	G2 (39)	0.0395	0.1109	-0.0797	0.5300
	G3 (14)	-0.0926	0.0825	-0.2496	0.0000
CGC	**G1 (40)**	0.0003	0.0033	-0.0079	0.0162
	G2 (39)	-0.0085	0.0172	-0.0761	0.0118
	G3 (14)	0.0586	0.0260	0.0198	0.1212
SC	**G1 (40)**	-0.0299	0.1114	-0.5430	0.1510
	G2 (39)	0.0202	0.1268	-0.1278	0.7656
	G3 (14)	-0.0068	0.0342	-0.0784	0.0672

The values between parentheses represent the number of units in each performance group.

Significant differences between distributions are present in the two periods. With respect to the 1998-2002 period, the decomposition results describe the units' behaviors as follows. Group 1 has the highest Luenberger indicator (*L*), being significantly superior to group 3, which is showing the worst results with respect to this measure. By looking at the decomposition (see also Figure 1.9), it is noticed that this result can be based on the significantly higher pure efficiency change (*PEC*). It is obvious from Figure 1.9 that this performance group is the only one with positive efficiency change (*EC*). Altogether, the efficiency change (*EC*) and pure efficiency change (*PEC*) suggest the good use of the inputs and outputs. Group 1 is also the only one with negative congestion change (*CGC*), but although this is significantly lower than the other two groups it is still quite close to zero. Additionally, no important scale change (*SC*) is present.

Table 1.4. Luenberger Decomposition: Group Level Li Test Results

1998-2002		L	TC	EC	PEC	CGC	SC
1-2	t-statistic	-0.9252	2.9869	-0.1241	8.4102	8.4075	-0.2935
	p-value	0.8226	0.0014*	0.5494	0.0000*	0.0000*	0.6154
1-3	t-statistic	1.6250	2.3543	-0.2561	15.0102	7.2367	0.5506
	p-value	0.0520*	0.0093*	0.6011	0.0000*	0.0000*	0.2909
2-3	t-statistic	1.4446	10.4305	-0.4754	1.2284	0.2787	1.8317
	p-value	0.0742*	0.0000*	0.6827	0.1097	0.3902	0.0335*
2002-2006		**L**	**TC**	**EC**	**PEC**	**CGC**	**SC**
1-2	t-statistic	2.4803	8.2849	3.5531	0.8777	1.5093	1.2334
	p-value	0.0065*	0.0000*	0.0002*	0.1901	0.0656*	0.1087
1-3	t-statistic	0.3478	5.9275	-0.4415	0.3129	19.6905	-0.1518
	p-value	0.3640	0.0000*	0.6706	0.3772	0.0000*	0.5603
2-3	t-statistic	-0.3185	1.4633	0.0702	1.8262	12.4554	-0.6496
	p-value	0.6250	0.0716*	0.4720	0.0339*	0.0000*	0.7420

*: Statistically significant differences

The second group is mainly defined by the significantly superior technological change (see 1998-2002 *TC* in Table 1.3 and Figure 1.9). Thus, this performance group includes the technological innovators, the ones that shift the frontier. Group 2 is also characterized by good average values of the Luenberger (*L*) and pure efficiency change (*PEC*) indicators. In the decomposition, the latter is complemented by positive congestion change (*CGC*) and negative scale efficiency change (*SC* is significantly inferior to group 3).

Finally, performance group 3 is significantly the worst in terms of the Luenberger (*L*) and technological change (*TC*) indicators. While it shows negative efficiency (*EC*) and pure efficiency changes (*PEC*), it scores positively in terms of scale efficiency change (*SC*). Indeed, regarding the scale efficiency change (*SC*), group 3 is on average the best cluster and significantly different from group 2. Ultimately, group 3 has a positive (but close to zero) congestion change (*CGC*).

Interpretations of the results are similar in the case of the period 2002-2006, even though the composition of the performance groups and the indicator values are slightly different. Banks in performance group 1 have by far the best results regarding technological change (*TC*). Even if the mean values of this component are not that dissimilar among the three clusters (see Table 1.4 and Figure 1.9), the Li test indicates there are significant differences among the distributions of these scores. Consequently, one could speculate that banking units in group 1 are leading the innovations and technological improvements. Moreover, one can also observe the downside of this technological change (*TC*), as this cluster suffers from important negative changes in efficiency (*EC*) and scale efficiency (*SC*). It may be that investments in new technologies affect the input-output use, leading banks in this group to operate at an inefficient scale.

Group 2 is projected as the best performer through the highest Luenberger indicator (*L*) and, after decomposing, experiences the highest efficiency (*EC*), pure efficiency (*PEC*) and scale efficiency (*SC*) changes (see Table 1.4 and Figure 1.9). Furthermore, concerning the last three indicators, cluster 2 is the only one with positive values throughout. Hence, group 2 is the leader with regard to inputs and outputs employment (see *EC* and *PEC*) and the management of scale efficiency (see *SC*). The results indicate that group 3 is formed by the worst performers. Even if so, in contrast to the negative pure efficiency change (*PEC*), the Luenberger (*L*) and technological change (*TC*) indicators present quite high positive shifts. What is more, the congestion change indicator (*CGC*) is significantly superior to the other two performance groups, an indication of improvements in labor utilization.

Appendix 1.1 contains graphical illustrations of the above Li tests. Each picture shows the densities of the contrasted Lunberger components. One can then visually observe when the null hypothesis of equality between the distributions are accepted or rejected. Furthermore, every figure has a caption stating the compared groups (the first one is represented by a solid line while the dotted line corresponds to the second) and the test outcome.

5.4. Linking Existing Performance Groups with Banking Ratios

Following this characterization of performance groups, the analysis attempts to reach more economically meaningful interpretations. In line with banking related strategic groups research (see Mehra 1996; Athanassopoulos 2003; Zúñiga-Vicente *et al.* 2004; Más-Ruiz *et al.* 2005; Ray and Das 2010), various dimensions of banks' activities are defined through ratios. The employed variables are specified as follows: (1) *ATMs*/Total Assets (level of employed technology), (2) No. of Branches/Total Assets (geographical reach, proximity to customers), (3) (Capital + Reserves)/Liabilities (risk aversion), (4) Interest Margin/No. of Employees (proxy 1 for performance), (5) return on assets (*ROA*) (proxy 2 for performance), and (6) return on equity (*ROE*) (proxy 3 for performance).[4]

By associating the above ratios with the performance groups, Tables 1.5 and 1.6 present the descriptive statistics and the test statistics. Analogous to Appendix 1.1, Appendix 1.2 shows the graphical illustration of the Li tests for these banking ratios. Interpreting the results, we observe that in 1998-2002 group 1 is significantly superior regarding the proximity to customers (number of branches divided by total assets). In

[4] All the ratios are averages between the two time periods they represent (*i.e.* 1998-2002 and 2002-2006).

addition, this performance group shares the leading position in terms of *ROA* with group 2. This is in line with the fact that this cluster is the one with the best Luenberger indicator (*L*) and pure efficiency change (*PEC*).

Table 1.5. Banking Ratios: Group Level Descriptive Statistics

1998-2002		Mean	Std. Dev	Min.	Max.
ATM/TA	**G1 (27)**	0.000064	0.000035	0.000000	0.000145
	G2 (29)	0.000049	0.000026	0.000000	0.000091
	G3 (40)	0.000036	0.000035	0.000000	0.000120
Branch/TA	**G1 (27)**	0.000063	0.000030	0.000001	0.000133
	G2 (29)	0.000046	0.000019	0.000013	0.000082
	G3 (40)	0.000048	0.000039	0.000000	0.000208
IntMarg/Empl	**G1 (27)**	89.8485	18.9074	54.2858	126.1127
	G2 (29)	117.7374	35.7944	71.3838	257.5769
	G3 (40)	78.8165	34.8450	6.0652	140.5075
Risk	**G1 (27)**	0.0908	0.0394	0.0526	0.2069
	G2 (29)	0.0910	0.0492	0.0509	0.3330
	G3 (40)	0.1077	0.0843	0.0270	0.4616
ROA	**G1 (27)**	0.0093	0.0100	-0.0143	0.0407
	G2 (29)	0.0112	0.0083	-0.0195	0.0367
	G3 (40)	0.0099	0.0110	-0.0304	0.0348
ROE	**G1 (40)**	0.0792	0.0661	-0.1017	0.2410
	G2 (39)	0.1001	0.0601	-0.1785	0.1756
	G3 (14)	0.0807	0.0790	-0.2256	0.2765
2002-2006		**Mean**	**Std. Dev**	**Min.**	**Max.**
ATM/TA	**G1 (40)**	0.000030	0.000025	0.000000	0.000110
	G2 (39)	0.000037	0.000027	0.000000	0.000091
	G3 (14)	0.000056	0.000019	0.000026	0.000096
Branch/TA	**G1 (40)**	0.000027	0.000017	0.000000	0.000071
	G2 (39)	0.000037	0.000023	0.000000	0.000126
	G3 (14)	0.000057	0.000027	0.000036	0.000144
IntMarg/Empl	**G1 (40)**	121.5403	84.2901	6.2577	513.1580
	G2 (39)	113.4744	44.8215	11.9998	187.5181
	G3 (14)	95.4188	18.1373	64.4998	134.9569
Risk	**G1 (40)**	0.1211	0.2062	0.0301	1.3488
	G2 (39)	0.1147	0.1023	0.0261	0.5246
	G3 (14)	0.0746	0.0129	0.0566	0.0954
ROA	**G1 (40)**	0.0085	0.0061	-0.0072	0.0287
	G2 (39)	0.0052	0.0233	-0.1271	0.0279
	G3 (14)	0.0081	0.0028	0.0009	0.0127
ROE	**G1 (40)**	0.0842	0.0480	-0.0773	0.1583
	G2 (39)	0.0820	0.0763	-0.2429	0.2378
	G3 (14)	0.0853	0.0282	0.0060	0.1154

The values between parentheses represent the number of units for each of the two bank types.

Group 2 is also significantly ahead concerning the interest margin per employee ratio, which makes it the best with respect to the performance measures. Its characterization by higher technological change (*TC*) can be related with a good outcome in the *ATMs* divided by total assets ratio (new technology use). Finally, the distribution of results define group 3 (the best in scale efficiency (*SC*) and congestion (*CGC*) changes) by a significantly higher risk ratio. It is notable that in the first period there are no significant differences in *ROE*.

Table 1.6. Banking Ratios: Group Level Li Test Results

1998-2002		ATM/TA	Branch/TA	IntMarg/Empl	Risk	ROA	ROE
1-2	t-statistic	1.1862	2.0643	1.7500	1.9076	-0.0899	0.2440
	p-value	0.1178	0.0194*	0.0401*	0.0282*	0.5358	0.4036
1-3	t-statistic	2.8309	1.9593	1.2515	1.5452	1.4487	0.7457
	p-value	0.0023*	0.0250*	0.1054	0.0611*	0.0737*	0.2279
2-3	t-statistic	3.5312	1.4237	2.9858	1.8801	2.8987	0.6675
	p-value	0.0002*	0.0773*	0.0014*	0.0300*	0.0019*	0.2522
2002-2006		**ATM/TA**	**Branch/TA**	**IntMarg/Empl**	**Risk**	**ROA**	**ROE**
1-2	t-statistic	0.8057	1.5894	-0.3467	-0.7213	-0.3679	-0.5221
	p-value	0.2102	0.0559*	0.6356	0.7646	0.6435	0.6992
1-3	t-statistic	3.0411	5.3988	2.3343	-0.1715	0.0712	-0.0161
	p-value	0.0012*	0.0000*	0.0098*	0.5681	0.4716	0.5064
2-3	t-statistic	1.1569	1.0685	2.7114	0.4788	0.5022	0.0009
	p-value	0.0836*	0.0926*	0.0034*	0.3160	0.3078	0.4996

*: Statistically significant differences

The second period performance group defined by technological change (*TC*) (group 1) is yet again the best in terms of interest margin per employee. This leadership in performance ratios is shared with group 2, defined through good managerial practices revealed by the Luenberger (*L*) and efficiency change (*EC*) indicators. Lastly, group 3 has significantly better results in relation to *ATMs* and number of branches divided by total assets. Additionally, this cluster has negative changes in efficiency (*EC*) and scale efficiency (*SC*), which may be a consequence of the investments dedicated to more *ATMs* and branches. Surprisingly, these are the only significant differences for this second period, as in risk, *ROA* and *ROE* the three performance groups have similar distributions.

6. Conclusions, Limitations and Future Lines of Research

This paper has empirically analyzed the productivity and efficiency of the Spanish private and savings banks over an eight-year period (1998-2006). Although this sector attracted vast amounts of interest in past research, the present study puts forward a new understanding of the phenomena. This is done by means of a decomposition of a Luenberger productivity indicator leading to productivity and managerial interpretations. This method, together with the use of the resulting productivity and efficiency changes as variables for cluster analysis, represents a novel conceptual and practical basis within this research field. Hence, the behavior of each banking group is identified through significant differences between performance groups in terms of the Luenberger indicator and its components. In this manner, the productivity and efficiency results and those of the cluster analysis are consistent with each other, an issue that attracted quite a lot of debate in the strategic groups' literature.

More specifically, one can observe, through five productivity dimensions, the banking performance both at the unit level as well as at the cluster level. The Luenberger indicator (*L*) is first decomposed into technological change (*TC*) and efficiency change (*EC*). The former shows the impact of innovatory practices in the shift of the best practice frontiers. The latter indicates the net result of the catching-up effect, *i.e.* whether the distance separating the frontier from the inefficient units has been expanded or contracted. Subsequently, this efficiency change (*EC*) is decomposed to isolate pure efficiency change (*PEC*), scale efficiency change (*SC*) and congestion change (*CGC*).

Our results first show that productivity and efficiency increases are higher in 2002-2006 than in 1998-2002. This is mainly due to the approximately 2-to-1 ratio between the Luenberger indicator (*L*) and the technological change (*TC*). Implicitly, these are signs of good employment of resources and the use of new information technologies. However, the second period negative values of pure efficiency change (*PEC*) and scale efficiency change (*SC*) could represent the pitfall of the first period expansion strategy.

Next, the global competition hypothesis is sustained by the fact that private and savings banks each dominate diverse components of the Luenberger decomposition. First, in 1998-2002, the savings banks perform better with respect to the Luenberger indicator (*L*) and technological change (*TC*). At the same time, private banks have better efficiency change (*EC*) and have no scale efficiency change (*SC*) issues. Hence, in the first period the innovations were mainly introduced by the savings banks involved in the expansion process. Second, the overall competition in the sector is even clearer in the second period, as no significant differences appear related to the Luenberger indicator (*L*). Whilst the technological change (*TC*) measure also shows roughly equal values, the private banks maintain better efficiency change (*EC*). What is interesting, is that the before mentioned 2-to-1 ratio between periods is mostly generated by the private banks. These show increases in the Luenberger (*L*) and technological change (*TC*) measures of even more than twice the first period.

The cluster analysis supports the initial findings and forms performance groups that encompass different types of banking units. At this point, one is able to see with more accuracy where technological innovators or good organizational practices are situated. As expected, the main discriminating variable is the technological change (*TC*). Accordingly, the clustering is consistent with the time and unit type analyses. In addition, the Luenberger (*L*) and pure efficiency change (*PEC*) indicators provide insights in the different managerial practices between the grouped units.

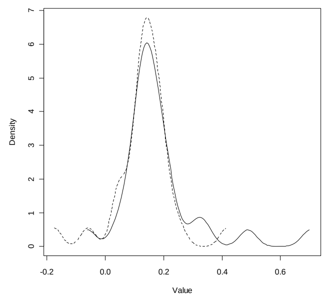
Finally, as suggested by the strategic groups' literature, economically meaningful interpretations were achieved by linking the performance groups with banking performance ratios. For instance, one observes that in 1998-2002 the group that showed the best results in the Luenberger indicator (*L*) is also leading in terms of proximity to customers. In 2002-2006, the leadership in performance ratios is shared among the technological innovators' group and the one defined through good managerial practices.

These results meet the requirements of the strategic groups' literature. Traditionally, clusters are considered meaningful when differences in performance ratios are achieved (see *e.g.* Amel and Rhoades 1988; Fiegenbaum and Thomas 1994). In our case, we have demonstrated that the devised performance groups are statistically different not only in terms of non-parametric frontier based productivity indicators but also with respect to banking ratios.

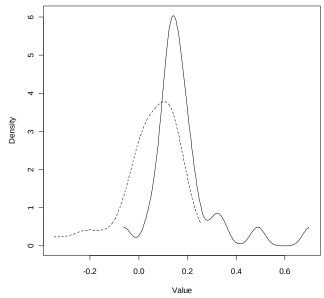
The proposed methods were devised in the framework of offering a comprehensive description of the evolution of the Spanish banking sector. Apart from the above findings, other interesting phenomena are revealed. Taking advantage of the deregulation, the savings banks initiated an important expansion process. The movement from the static market situation to the growth phase created congestion issues in the labor input. These have been solved by investments in new technologies dedicated to the high number of branches that had to be organized. According to the analyzed time-periods, local scale economies appear to have been exhausted (thus, no efficiency gains seem to remain possible from internal growth). In this respect, future research could thus be directed to branch network optimization through potential mergers and acquisitions aimed at increases in efficiency. These operations could have a positive impact not only on the scale efficiency, but also on the scope efficiency of the Spanish banking industry.

Obviously, each empirical work must acknowledge its methodological and sample related limitations. First, the time-span of the sample can be enlarged. Second, international comparisons could be introduced when certain similarities in behaviors can be encountered. These are among the issues that could be fruitful avenues for future work.

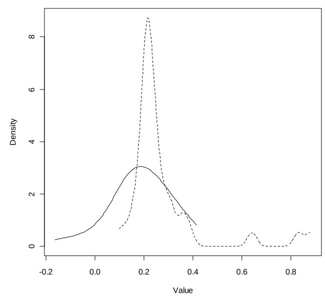
Appendix 1.1. Luenberger Components' Distributions: Li Test (selection)



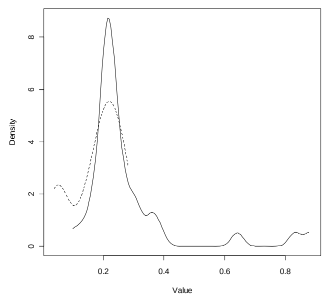
Luenb 1998-2002; G1-G2: H_0 accepted



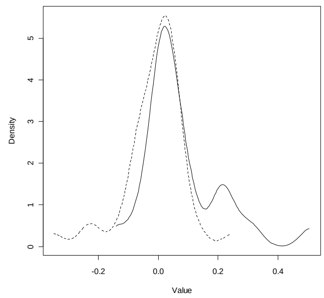
Luenb 1998-2002; G1-G3: H_0 rejected



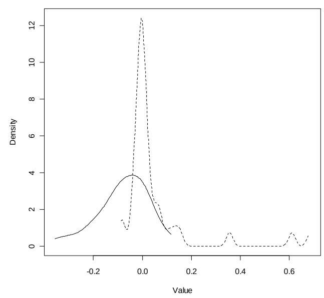
Luenb 2002-2006; G1-G2: H_0 rejected



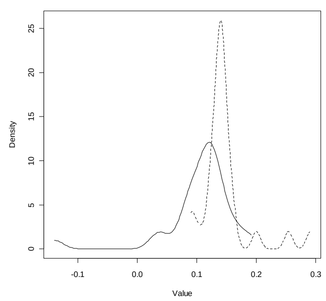
Luenb 2002-2006; G2-G3: H_0 accepted



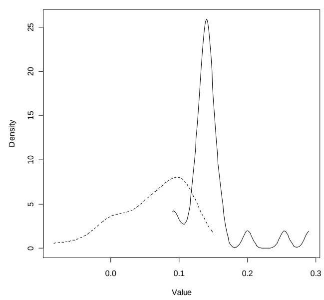
EC 1998-2002; G1-G3: H_0 accepted



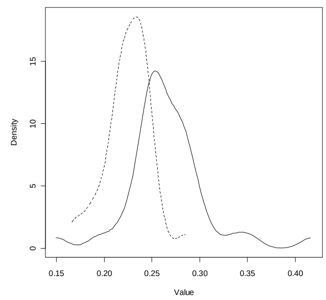
EC 2002-2006; G1-G2: H_0 rejected



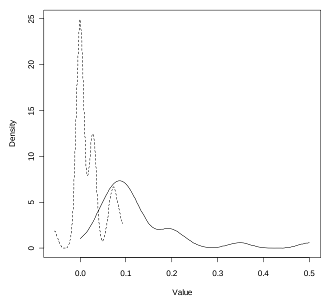
TC 1998-2002; G1-G2: H_0 rejected



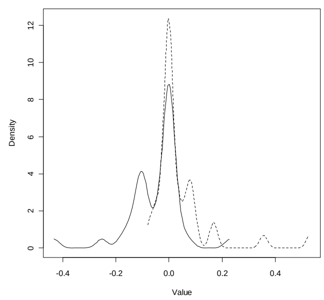
TC 1998-2002; G2-G3: H_0 rejected



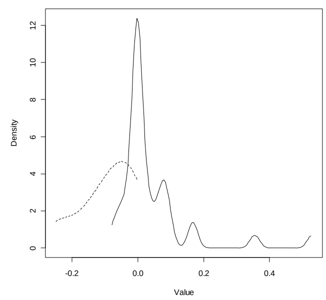
TC 2002-2006; G1-G2: H_0 rejected



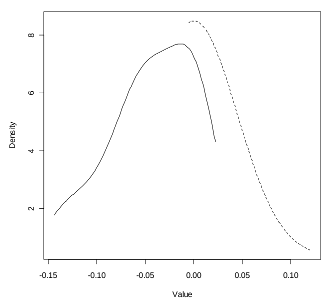
PEC 1998-2002; G1-G2: H_0 rejected



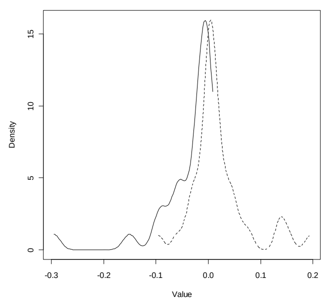
PEC 2002-2006; G1-G2: H_0 accepted



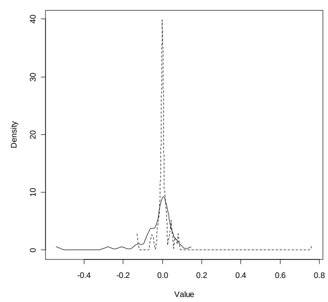
PEC 2002-2006; G2-G3: H_0 rejected



CGC 1998-2002; G1-G2: H_0 rejected

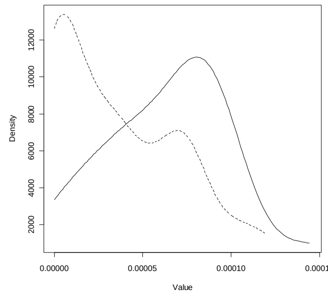


SC 1998-2002; G2-G3: H_0 rejected

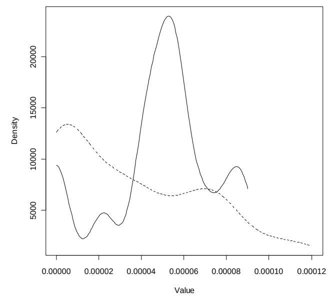


SC 2002-2006; G1-G2: H_0 accepted

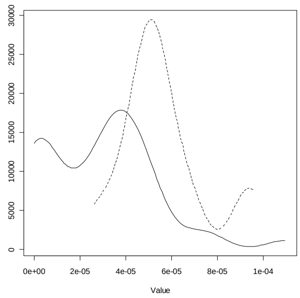
Appendix 1.2. Banking Ratios' Distributions: Li Test (selection)



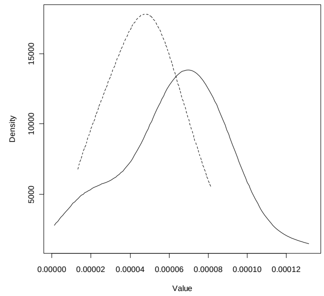
ATM/TA 1998-2002; G1-G3: H_0 rejected



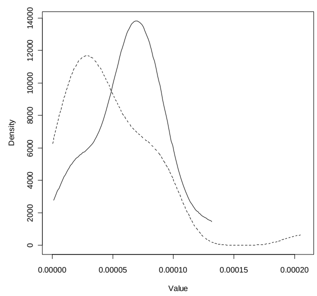
ATM/TA 1998-2002; G2-G3: H_0 rejected



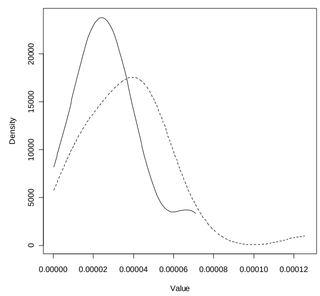
ATM/TA 1998-2002; G1-G3: H_0 rejected



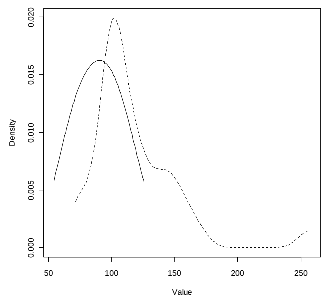
Branch/TA 1998-2002; G1-G2: H_0 rejected



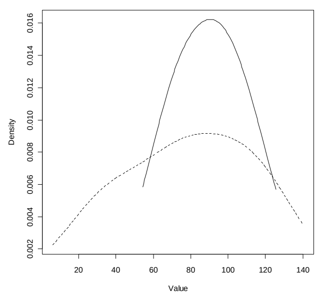
Branch/TA 1998-2002; G1-G3: H_0 rejected



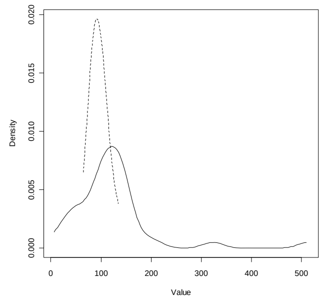
Branch/TA 2002-2006; G1-G2: H_0 rejected



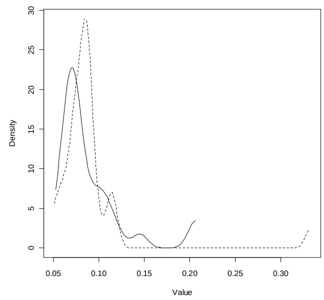
IntMa/Emp 1998-2002; G1-G2: H_0 rejected



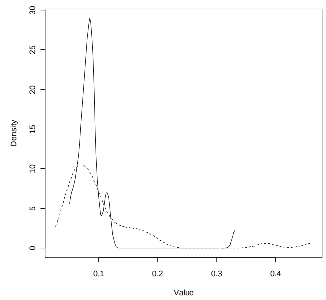
IntMa/Emp 1998-2002; G1-G3: H_0 rejected



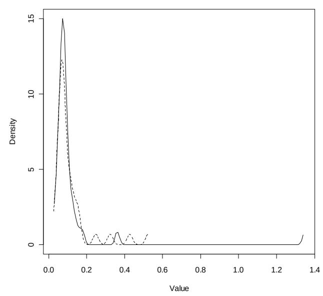
IntMa/Emp 2002-2006; G1-G3: H_0 rejected



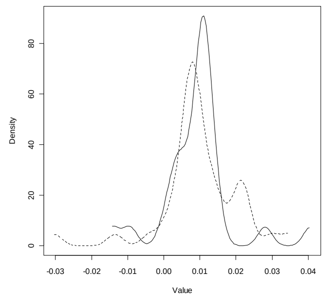
Risk 1998-2002; G1-G2: H_0 rejected



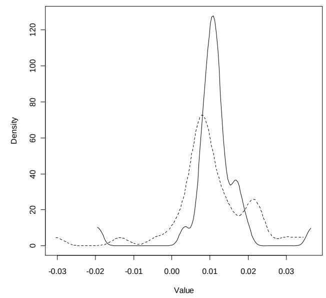
Risk 1998-2002; G2-G3: H_0 rejected



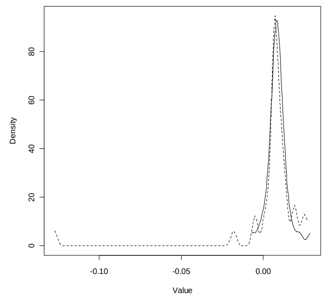
Risk 2002-2006; G1-G2: H_0 accepted



ROA 1998-2002; G1-G3: H_0 rejected



ROA 1998-2002; G2-G3: H_0 rejected



ROA 2002-2006; G1-G2: H_0 accepted

Chapter 2:

Technology-Based Total Factor Productivity and Benchmarking: New Proposals and an Illustration

Abstract

The present study fills a gap between the benchmarking literature and multi-output based efficiency and productivity studies by proposing a benchmarking framework to analyze total factor productivity (*TFP*). Different specifications of the Hicks-Moorsteen TFP index are tailored for specific benchmarking perspectives: (1) static, (2) fixed base and unit, and (3) dynamic TFP change. These approaches assume fixed units and/or base technologies as benchmarks. In contrast to most productivity indices, the standard Hicks-Moorsteen index always leads to feasible results. Through these specifications, managers can assess different facets of the firm's strategic choices in comparison with firm-specific relevant benchmarks and thus have a broad background for decision making. An analysis for the Spanish banking industry between 1998 and 2006 serves to illustrate the feasibility and managerial implications of the proposed framework.

Keywords: Benchmarking, DEA, total factor productivity, Hicks-Moorsteen index, competition, Banking.

1. Introduction

Literature refers to benchmarking fundamentally as the selection of a unit of strategic value, against which performance is compared (Camp 1998). Also, important amounts of academic studies introduce measures of multiple inputs and outputs that analyze the efficiency and productivity of firms. Nevertheless, so far there seems little or no link between these two streams of research. In this paper we propose a way of bridging this gap by defining novel total factor productivity (*TFP*) benchmarking methods. These are devised to include cross-sectional and inter-temporal perspectives not only concerning unit to unit benchmarking, but also efficiency frontier benchmarking. Accordingly, the manager is provided with a new set of broad benchmarking tools for decision making. These various perspectives are introduced stepwise starting with static indices, continuing with fixed base and unit, and ending with dynamic benchmarking. Moreover, these *TFP* benchmarking indices are relevant to any industry. By way of example, this benchmarking methodology is illustrated within the Spanish banking sector.

Both benchmarking and *TFP* analysis represent key tools in business economics. For instance, Balk (2003) points to two main actions a manager constantly carries out: the monitoring activity (*i.e.*, assessing how the firm is doing over time) and the benchmarking activity (*i.e.*, comparing firm performance with respect to its main competitors). Although both activities aim at enhancing performance, monitoring is internally oriented while benchmarking has an external focus.

Benchmarking is defined as the search and emulation of the industry's best practices and it thus is an objective setting procedure (Camp 1998). It was pioneered by Xerox which in 1980 compared its photocopier production in the United States with the one of the Japanese Fuji-Xerox. This was followed by a widespread adaptation by firms seeking improvements (Voss *et al.* 1997). Through benchmarking, a firm can deduce whether it has a best or worst practice. Consequently, it can aim at maintaining superiority or at closing the gap to its competitors (Camp 1998; Cokins 2004). Therefore, benchmarking appeals most to firms with similar strategic orientations or facing comparable problems and opportunities (Smith 2005; Collis *et al.* 2007).

Due to its importance, management studies include benchmarking as a main phase of the performance measurement and analysis of the firm. In decision making, benchmarking can be used for data analysis and testing hypotheses prior to selecting alternative strategies (Smith 2005; Franceschini *et al.* 2007). Furthermore, benchmarking is an important motivating tool for management (Langfield-Smith 2005; Smith 2005). Identifying challenging benchmarks provides positive motivation and should be part of the management control and reward system (Langfield-Smith 2005). Benchmarking helps to improve performance, but also fosters the learning and understanding of new best practices (Voss *et al.* 1997; Smith 2005). In turn, the achieved knowledge can be helpful for activity planning aimed at enhancing competitive advantage (Pryor and Katz 1993).

Empirical applications suggest different methods for monitoring or benchmarking activities. In managerial studies of performance, the simplest method is the use of output-input ratios or any other kind of ratios for that matter (see Banker *et al.* 1996; Bragg 2002). Managers care about profitability and implicitly about productivity; "the most encompassing measure of productivity change, *TFP* change, is nothing but the ''real'' component of profitability change. Put otherwise, if there is no effect of prices then productivity change would coincide with profitability change." (Balk 2003: 6). For instance, in the one output one input case, *TFP* is given by the division of output (y) over input (x). Following, *TFP* change (or the index of *TFP*) is the division of productivity in period $t+1$ to the one in t (*i.e.,* $(y_{t+1}/x_{t+1})/(y_t/x_t)$) (see definitions in American Productivity Center (*APC*) 1981, Miller 1984, or the more recent review in Balk 2003). Results higher than unity indicate *TFP* increases, whereas values lower than one point to decreases in *TFP*.

The above *TFP* measures are easily adaptable to benchmarking purposes. One can simply divide the firm's *TFP* change (or performance) ratio to the one of a chosen competitor. Computing performance or *TFP* measures in this fashion is straightforward and rather attractive. However, in multiple inputs and outputs technologies various problems emerge related to the use of ratios for benchmarking. When comparing two firms, different partial productivity ratios (built by dividing different outputs by some inputs) can point to different results. These ratios are generally constructed to illustrate a certain aspect of firm (strategic) performance. However, due to the fact that each ratio accounts for a dissimilar input and/or output, these ratios disregard to a certain extent global performance. This makes the interpretation of partial productivity results difficult as contradictory firm level results usually appear from the comparison with a benchmark. In addition, given the lack of an underlying theoretical model, it is usually rather complicated to understand the mechanisms generating the results.

Management literature suggests a way to remedy this problem. Specifically, in the presence of prices, multiple outputs and inputs indices are proposed by the *APC* method (APC 1981; Miller 1984). This proposal employs output and input quantities and prices together (taking prices as weighs for adding output and input quantities) with components from Laspeyres, Paasche and Fisher indices to account for the changes in productivity.

Turning attention to efficiency and productivity analysis, this literature utilizes frontier methods to handle multiple inputs and outputs situations. These non-parametric techniques have known an important upsurge in recently and are probably, best known under the label Data Envelopment Analysis (*DEA*) (see Färe *et al.* 1994; Ray 2004). *DEA* methods compute the degree of inefficiency separating a certain Decision Making Unit (*DMU*) from the efficiency frontier. In this case, the comparison is done against the whole analyzed sample, not against some specific strategic competitor as in benchmarking. On this topic, Berger and Humphrey (1997: 175) state that "at its heart, frontier analysis is essentially a sophisticated way to benchmark the relative performance of production units". Thus, in *DEA* benchmarks are the efficient units on the frontier against which all the others are projected using some efficiency measure (see Färe *et al.* 1994; Ray 2004). Therefore, it is very unlikely that a single benchmark is found for all units evaluated in the sample. In contrast to partial productivity ratio benchmarking, *DEA* represents a more theoretically sound method to compute. Furthermore, it is easier to interpret since it employs a model with an economic underpinning in production theory.

In inter-temporal analyses, the efficiency and productivity literature captures the potentially shifting efficiency frontier usually through index numbers. For instance, the geometric mean Malmquist productivity index is probably the best known measure that has been extensively used in past research (see the surveys of Färe *et al.* 1998, and Fethi and Pasiouras 2010).

However, there are some pitfalls to the use of Malmquist indices. First, it is not always a *TFP* index: while the *TFP* properties are maintained under constant returns to scale, shortcomings appear in the presence of variable returns to scale which mostly represents the true technology (Grifell-Tatjé and Lovell 1995). Second, there is the possibility of having infeasible results. For example, Glass and McKillop (2000) find infeasibilities for up to 7% of the analyzed UK building societies. Yörük and Zaim

(2005) report infeasible computations that reach 10% of their sample of OECD countries. Also, for the Spanish insurance industry Cummings and Rubio-Misas (2006) mention that infeasibilities are present (without indicating the exact amount). This issue could have an important impact on benchmarking analysis, as managers wish to obtain firm level results that may not always be available.

As a result, there are two main issues with the Malmquist index that need to be resolved: *TFP* interpretation and infeasibilities. To address these problems, one can turn to Bjurek's (1996) proposal for a Hicks-Moorsteen *TFP* (*HMTFP*) index (see also Lovell 2003: footnote 18). Instead of adopting an input- or output-orientation (as Malmquist indices usually do), the *HMTFP* is a simultaneously output- and input-oriented index. More precisely, it measures the change in output quantities in the output direction and the change in input quantities in the input direction. The *TFP* characteristics of the *HMTFP* index provide a solution to the limitations of the traditional Malmquist productivity index in the presence of flexible returns to scale. Furthermore, this *HMTFP* index is well-defined under general assumptions of variable returns to scale and strong disposability.[5] However, in spite of its attractive properties, the *HMTFP* has been scarcely empirically applied.[6]

Various benchmarking applications have been developed in the non-parametric efficiency and productivity analysis framework by isolating reference frontiers or *DMUs*. In the non-*TFP* context, Berg *et al.* (1992) adapt the Malmquist productivity

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[5] Briec and Kerstens (2010) demonstrate that the Hicks-Moorsteen productivity index satisfies the determinateness property under mild conditions. According to Bjurek (1996: 310) the feasibility of this index is attributable to the property that "all input efficiency measures included meet the condition that the period of the technology is equal to the period of the observed output quantities" and "all output efficiency measures included meet the condition that the period of the technology is equal to the period of the observed input quantities".

[6] To the best of our knowledge, there is only one more empirical application/decomposition of Bjurek's Hicks-Moorsteen index (1996). This was developed (in a parametric context) by Nemoto and Goto (2005).

index to have a base year frontier as a benchmark frontier, and measure productivity growth or regress relative to this fixed basis. Also, single benchmark *TFP* analyses have been undertaken by Zaim *et al.* (2001), Färe *et al.* (2004) and Zaim (2004). Manipulating a Hicks-Moorsteen index, their proposals include both cross-sectional and inter-temporal analyses by mixing a single *DMU* and *TFP* benchmarking. Zaim *et al.* (2001) use a five years sample of OECD countries to analyze the well-being of individuals in each country as compared to a benchmark country. Similarly, environmental performance is measured against a benchmark *DMU* in Färe *et al.* (2004) and Zaim (2004). While the former study looks upon OECD countries at cross-sectional level, the latter analyzes US states from both cross-sectional and inter-temporal perspectives.

A small existing literature thus proposes efficiency frontier comparisons using productivity indices combined with some form of unit to unit benchmarking. But, while consensus is reached regarding the usefulness of benchmarking, far less agreement exists with respect to the choice of benchmarks. In a strategic analysis setting, the interest of a firm may be to know its relative performance to a certain specific competitor, instead of comparing itself to a frontier potentially composed of all firms in the sector. The benchmark could differ for each firm, even though it could remain the same over a certain time period. Additionally, awareness of *TFP* positioning is useful in both static and dynamic environments. Efficiency coefficients (static) and *TFP* indices (dynamic) relative to a given benchmark are equally relevant and could represent the basis of strategic decision-making. For instance, in the case of similar strategic configurations, firms constitute strategic groups and may choose their benchmark within their relevant cluster. In this case, the benchmark unit can be the leader of the strategic group or any other unit, say the local competitor, regardless of its performance.

To develop a systematic framework to analyze these issues, the present study proposes a *TFP* benchmarking framework illustrated for the Spanish banking sector. This task is undertaken through an adaptation of Bjurek's (1996) *HMTFP* index for benchmarking purposes. The introduced *HMTFP* indices for benchmarking include the features of the traditional *HMTFP* together with some of the properties of the indices in Berg *et al.* (1992), Zaim *et al.* (2001), Färe *et al.* (2004) and Zaim (2004). Accordingly, various specifications of the *HMTFP* index are tailored to measure distances (and catching-up effects) between analyzed *DMUs* and their selected benchmarks. All these indices offer *TFP* interpretations with respect to static, fixed base or changing efficiency frontiers.

The empirical illustration considers the Spanish banking sector over the time period 1998-2006. This period is of particular interest, as it represents the beginning of a post-deregulation growth phase. The sector experienced consistent growth following the disappearance of the regulatory constrains and due to the overall competition between private and savings banks. In productivity and efficiency terms, the sector has been looked at through a vast array of research perspectives (*e.g.,* Grifell-Tatjé and Lovell 1996, 1997a, b; Lozano-Vivas 1997; Prior 2003; Tortosa-Ausina 2003, 2004; Crespí *et al.* 2004; Zúñiga-Vicente *et al.* 2004; Más-Ruiz *et al.* 2005; Prior and Surroca 2006; Tortosa-Ausina *et al.* 2008). However, to the best of our knowledge, there is no research available on *TFP* benchmarking.

This paper is structured as follows. Section 2 develops the *HMTFP* index adapted to benchmarking purposes. Section 3 presents sample information together with the variables and methods of analysis. The empirical illustration is found in Section 4, while the final section is dedicated to the concluding remarks.

2. The Hicks-Moorsteen *TFP* Index Adapted to Benchmarking

2.1. The Hicks-Moorsteen TFP Index and Its Interpretation

Caves *et al.* (1982) introduced the Malmquist index into the mainstream literature as a ratio of either output or input distance functions. This index is based on technology information only (*i.e.,* output and input quantities) and requires no price information. Furthermore, this index is always partially oriented (either output or input). Following some cursory remarks in the earlier literature (see Lovell 2003: 437), Bjurek (1996) introduces the technology-based Hicks-Moorsteen productivity index that combines output and input quantity indices defined using output and input distance functions respectively, making it simultaneously oriented.

Let us define an input vector $\mathbf{x} \in R_{+}^{N}$ and an output vector $\mathbf{y} \in R_{+}^{M}$ forming the technology T of feasible input-output combinations. The input distance function is defined as:

$$D_i\left(\mathbf{x},\mathbf{y},t\right)=\sup_{\theta}\left\{\theta>0:\left(\mathbf{x}/\theta,\mathbf{y},t\right)\in T\right\}. \tag{1}$$

The input distance function "treats (multiple) outputs as given, and contracts input vectors as much as possible consistent with the technological feasibility of the contracted input vector" (Färe *et al.* 1994: 10). This function presents a complete description of the structure of multi-input, multi-output efficient production technology. Furthermore, it offers "a complete characterization of the structure of multi-input, multi-output efficient production technology, and it provides a reciprocal measure of the distance from each producer to that efficient technology" (Färe *et al.* 1994: 10).

The output distance function can be defined as:

$$D_o\left(\mathbf{x},\mathbf{y},t\right)=\inf_{\phi}\left\{\phi>0:\left(\mathbf{x},\mathbf{y}/\phi,t\right)\in T\right\}. \tag{2}$$

This output distance function has similar characteristics, and can be equally employed to characterize the structure of efficient production technologies in the multi-output case (Färe *et al.* 1994). These distance functions can be defined using general specifications of technology (*e.g.*, a non-parametric technology with variable returns to scale).

The basic *HMTFP* index (Bjurek 1996) based on a technology in year t and computing changes between observations in periods t (y_t,x_t) and $t+1$ (y_{t+1},x_{t+1}) is defined as follows:

$$HMTFP_t = \frac{D_t^o(y_{t+1}, x_t) / D_t^o(y_t, x_t)}{D_t^i(y_t, x_{t+1}) / D_t^i(y_t, x_t)} \tag{3}$$

In line with Bjurek's (1996) proposal, the above distance functions are evaluated with respect to a technology assuming variable returns to scale (*VRS*) and strong disposability of inputs and outputs. The *HMTFP* index shows the shifts in the technology between two analyzed periods, both compared against the technology in the first year. The *HMTFP* scores are to be read in line with other ratio-based indices: specifically, values greater than one indicate *TFP* growth, whereas values lower than one point to decreases in *TFP*.

In the one input one output case, *TFP* is equal to the division of a single output over a single input (y/x), whereas *TFP* change is productivity in $t+1$ divided by productivity in t $((y_{t+1}/x_{t+1})/(y_t/x_t))$ (see APC 1981; Miller 1984; Balk 2003). In the multiple inputs and outputs case, a *TFP* index obtains a similar interpretation for a general technology (see Grifell-Tatjé and Lovell 1995; Balk 2003). Consequently, it takes account of all real production factors (inputs) compared to the real output vector (Balk 2003). Thus, the *HMTFP* is among the few frontier-based index numbers having a correct *TFP* interpretation. In the remainder, it is shown via a numerical example how the *HMTFP* is computed and how these results maintain a general *TFP* interpretation.

Let us consider a simple numerical example consisting of 5 fictitious units observed in two time periods (*t* and *t+1*) producing one output with one input (see Table 2.1). Following Bjurek *et al.* (1998) one can compute (using expression (3) and Figure 2.1) the *HMTFP* index for each *DMU*. For instance, the *HMTFP* corresponding to *DMU* 4 can be numerically expressed as:

$$HMTFP_{(DMU\,4)} = \frac{(6/4)/(2/4)}{(10/5)/(8/5)} = \frac{3}{1.25} = 2.4 \tag{4}$$

Figure 2.1. Illustration of the *HMTFP*

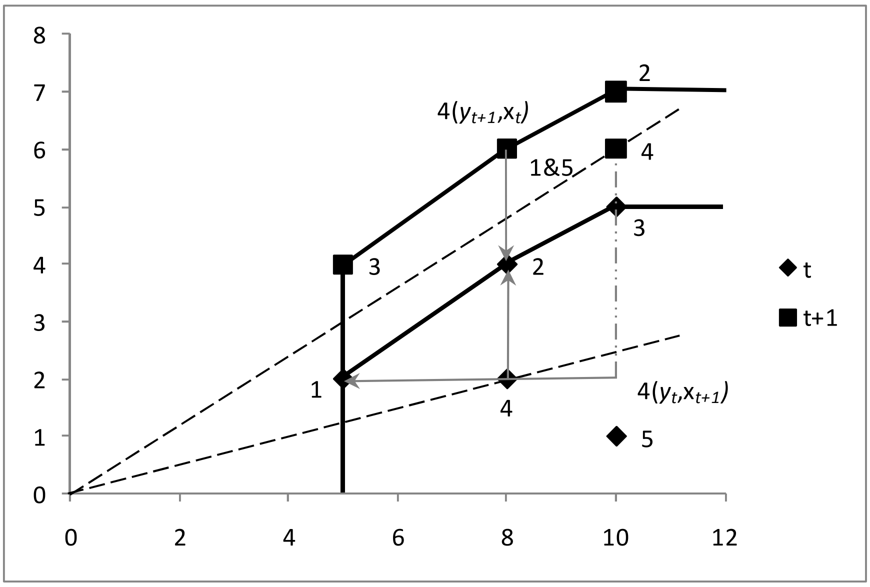


Table 2.1. The *HMTFP* Index: Numerical Example

(Panel A)

Period (1)	*DMU* (2)	Output (3)	Input (4)	*HMTFP* numer. (5)	*HMTFP* denomin. (6)	*HMTFP* (7)	Productivity (output / input) (8)	Productivity change (Prod t+1 / Prod t) (9)
t	1 (B)	2	5	-	-	-	0.4	-
t	2	4	8	-	-	-	0.5	-
t	3	5	10	-	-	-	0.5	-
t	4	2	8	-	-	-	0.25	-
t	5	1	10	-	-	-	0.1	-
t+1	1 (B)	6	8	3	1.6	1.875	0.75	1.875
t+1	2	7	10	1.75	1.25	1.4	0.7	1.4
t+1	3	4	5	0.8	0.5	1.6	0.8	1.6
t+1	4	6	10	3	1.25	2.4	0.6	2.4
t+1	5	6	8	6	0.8	7.5	0.75	7.5

The grey arrows in Figure 2.1 illustrate the distance functions in expression (4). For the output quantity index, the distance functions $D_t^o(y_{t+1},x_t)$=(6/4) and $D_t^o(y_t,x_t)$=(2/4) are given by the movement in the output direction from the coordinates (y_{t+1},x_t)=(6,8) and (y_t,x_t)=(2,8) respectively towards the frontier in *t*. *DMU* 4's output levels, 6 in *t+1* and 2 in *t*, both project vertically onto the benchmark level of 4 (defined by unit 2). Hence, the output quantity index is (6/4)/(2/4)=3, indicating the output level in *t+1* is three times the output level in *t*. Similarly, the input quantity index computes the input distance functions $D_t^i(y_t,x_{t+1})$=(10/5) and $D_i^t(y_t,x_t)$=(8/5). These reflect movements in the input direction from the points (y_t,x_{t+1})=(2,10) and (y_t,x_t)=(2,8) respectively to the input frontier in *t* (defined by unit 1). Consequently, *DMU* 4's input levels of 10 in *t+1* and 8 in *t* have an associated benchmark level of 5, producing the input quantity index of (10/5)/(8/5)=1.25 (this means that the input level in *t+1* is 25% bigger than in *t*). By dividing the output and input quantity indices, the $HMTFP_{(DMU4)}$ is 3/1.25=2.4, indicating a *TFP* growth of 140% between the two periods (see also columns 5, 6 and 7 in Table 2.1, Panel A).

Using the same numerical example with one input and one output (see columns 1 to 4 in Table 2.1, Panel A), productivity can be easily calculated as the ratio of output over input: (y/x) (see column 8 in Table 2.1, Panel A). Furthermore, productivity change is the ratio of productivity in *t+1* and the one in *t*: $(y_{t+1}/x_{t+1})/(y_t/x_t)$ (see column 9 in Table 2.1, Panel A). Therefore, one can now observe how the *HMTFP* index corresponds to the productivity change as traditionally understood (say, productivity ratio in *t+1* over productivity ratio in *t*, (6/10)/(2/8)=2.4, see APC 1981; Miller 1984). These values represent the slopes of the corresponding rays through the origin for the various *DMUs*. First, one notes that the *TFP* of *DMU* 4 in period *t+1* is higher than the one in period *t*, representing positive *TFP* change (compare the slopes of both dashed lines in Figure 2.1). Second, the slope of *DMU* 4 in period $t+1$ (6/10) divided by the slope of the same unit in t (2/8) yields exactly the outcome 2.4, the same result as in expression (4).

While the *HMTFP* index coincides with the traditional *TFP* interpretation, it also reveals one aspect that ratios are not able to show: information referring to the efficiency frontier. This is shown by the numerator and the denominator of the index. First, the output quantity index provides in the output direction an efficient benchmark of 4 (corresponding to *DMU* 2 in t). At the same time, expression (3) shows that *DMU* 4 is not efficient in the initial time period ($D_t^o(y_t,x_t)$=(2/4)=0.5). Second, in the input direction, one finds 5 as the benchmark point (corresponding to *DMU* 1 in t) and also the information about the input inefficiency in the initial year ($D_i^t(y_t,x_t)$=(8/5)=1.6). These movements on the output or input side represent the distances needed to reach a specific point on the best practice frontier.

All the above measurements are done with respect to the technology in the first year. Establishing a one year technology instead of selecting a geometric mean index is common practice in the benchmarking literature (see the Malmquist index in Berg *et al.* (1992) or the *HMTFP* index in Zaim *et al.* (2001), Färe *et al.* (2004) and Zaim (2004)). For instance, Berg *et al.* (1992) make use of a base technology to obtain a fixed benchmark for measuring technical change. Likewise, Zaim *et al.* (2001) propose an improvement index defined through a one year technology and using as benchmark a *DMU* in the analyzed time period. In line with the above authors, the reason not to combine technologies is quite straightforward: when performing benchmarking analysis the benchmark should be well determined and easy to identify.

There is one more aspect worthwhile mentioning. Criticism can be targeted to the pseudo-observations created by the *HMTFP* index, some of whose components are defined by including different time periods in the same distance function. This can be observed in expression (3) where outputs in periods *t+1* or *t* are combined with inputs in periods *t* or *t+1* respectively. Nevertheless, these mixed time periods are a main characteristic of the *HMTFP* index and contribute to both its *TFP* interpretation as well as to its feasibility. These combinations can further appear in benchmarking adaptations in the form of distance functions containing outputs (inputs) from one *DMU* and inputs (outputs) from another.

2.2. Adapting the HMTFP Index to Benchmarking Purposes: Three Proposals

It is now important to clearly delimitate possible benchmarking approaches. While the introductory section explains the motives for choosing a single unit as a benchmark, there are still pros and cons for each possible specification. The adaptations of the *HMTFP* index for benchmarking compare the productivity of two different *DMUs* in a variety of contexts. First, a static index provides a distance between analyzed *DMUs* and their benchmark. Second, the comparison is done against a fixed *DMU* and a base technology frontier. This is useful for situations in which managers achieve a good understanding of a competitor in a certain time period, and by iterating computations over the years they can observe the eventual catching-up effects that have been attained. Third, the dynamic benchmarking perspective is developed by contrasting *TFP* changes between analyzed *DMUs* and their benchmarks while allowing for both to evolve over time. The latter definition is novel in the efficiency benchmarking literature and helpful to capture catching-up effects which account for changes in technology.

2.2.1. The Static HMTFP Index for Benchmarking

The static adaptation of the *HMTFP* index for benchmarking can be mathematically expressed as follows:

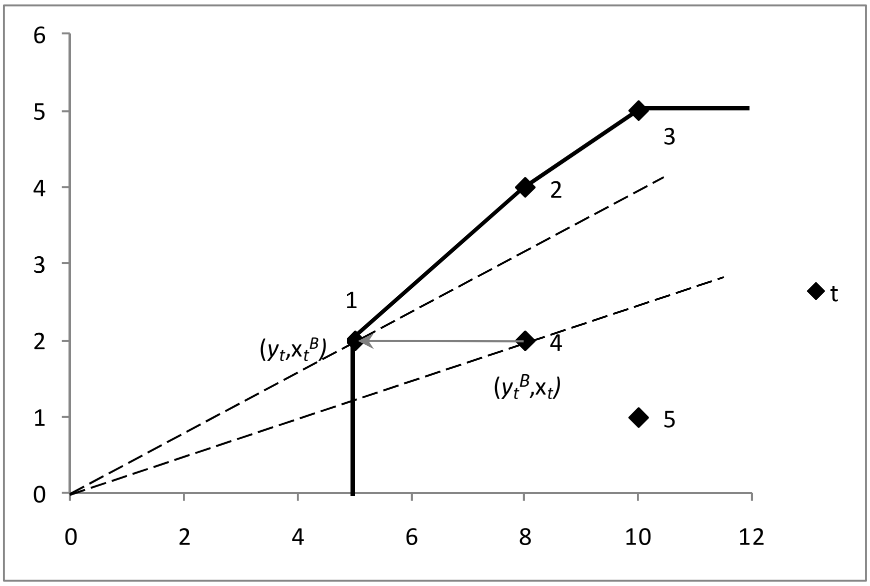
$$HMTFP_{st_t} = \frac{D_t^o(y_t, x_t^B) / D_t^o(y_t^B, x_t^B)}{D_t^i(y_t^B, x_t) / D_t^i(y_t^B, x_t^B)} \tag{5}$$

where t is the only period under analysis, (y_t, x_t) are the outputs and inputs of the analyzed *DMU* in period t, and (y_t^B, x_t^B) are the outputs and inputs of the unit established as a benchmark.

This specification of the *HMTFP* index permits one to compute, for a certain period t, the distance from each *DMU* to an established benchmark point (B). Let us return to the example in Table 2.1 (Panel B), now illustrated in Figure 2.2. Using expression (5), for *DMU* 4 in period t, the $HMTFP_{st}$ is given by:

$$HMTFP_{st(DMU\,4)} = \frac{(2/2)/(2/2)}{(8/5)/(5/5)} = \frac{1}{1.6} = 0.625 \tag{6}$$

Figure 2.2. Illustration of the Static *HMTFP* for Benchmarking



In Figure 2.2, the distance functions can be illustrated by arrows as in the case of the general *HMTFP*. However, it can be easily seen that the output-input combinations given by (y_t,x_t^B)=(2,5) and (y_t^B,x_t^B)=(2,5) position themselves on the efficiency frontier. Thus, in both output and input directions the associated distance functions (*i.e.,* $D_t^o(y_t,x_t^B)$=(2/2), $D_t^o(y_t^B,x_t^B)$=(2/2) and $D_t^i(y_t^B,x_t^B)$=(5/5)) are equal to 1. When computing $D_t^i(y_t^B, x_t)$=(8/5), the input level of 8 related to *DMU* 4 in period *t* is divided by the input direction benchmark level of 5, corresponding to *DMU* 1. Having an output quantity index of (2/2)/(2/2)=1 and an input quantity index of (8/5)/(5/5)=1.6, the $HMTFP_{st(DMU4)}$=0.625 (see also columns 5, 6 and 7 in Table 2.1, Panel B).

Table 2.1. (Panel B)

Adapting the *HMTFP* to Benchmarking: Numerical Example for the Static Case

Period (1)	*DMU* (2)	Output (3)	Input (4)	Static *HMTFP* numer. (5)	Static *HMTFP* denomin. (6)	Static *HMTFP* (7)	Productivity to benchmark (Prod *DMU* / Prod Bench) (per period) (8)
t	1 (B)	2	5	1	1	1	1
t	2	4	8	2	1.6	1.25	1.25
t	3	5	10	2.5	2	1.25	1.25
t	4	2	8	1	1.6	0.625	0.625
t	5	1	10	0.5	2	0.25	0.25
t+1	1 (B)	6	8	1	1	1	1
t+1	2	7	10	1.167	1.25	0.933	0.93
t+1	3	4	5	0.67	0.625	1.067	1.067
t+1	4	6	10	1	1.25	0.8	0.8
t+1	5	6	8	1	1	1	1

The interpretation of expression (6) is that, in period *t*, there is a distance of 1–0.625=0.375 between *DMU* 4 and the benchmark. Conversely, *DMU* 2 has a bigger than unity score (see column 7 in Table 2.1, Panel B). Its understanding is that this *DMU* is better positioned than the benchmark point. Similarly to the general specification of the index, the denominator and the numerator of the $HMTFP_{st(DMU4)}$ include the efficiency frontier component. In this case, the numerator value of 1 indicates no differences between *DMU* 4 and its benchmark in the output direction.

In the one input one output situation of Table 2.1, the result of expression (6) is equal to the one obtained by simply dividing the productivities of the analyzed *DMUs* 4 and 1 (column 8 in Table 2.1, Panel B). The distance between *DMU* 4 and its benchmark is 0.25/0.4=0.625. In the same way as for the classical *HMTFP*, Figure 2.2 illustrates the two slopes that are compared (in the one input one output case). The higher positioned slope of the benchmark corresponds to the better outcome of *DMU* 1 compared to *DMU* 4, which can be computed by dividing the two slopes, (2/8)/(2/5)=0.625. In addition, as seen in Table 2.1 (Panel B), this static index can be computed year by year.

2.2.2. The Fixed Base HMTFP Index for Benchmarking

The above static *HMTFP* index for benchmarking (see similar applications in Färe *et al.* 2004 or Zaim 2004) has, however, one pitfall: it does not include a time component. Traditionally, this problem was solved by defining a base year (benchmark technology) dynamic index (see, *e.g.*, the fixed base Malmquist index in Berg *et al.* 1992). By combining the fixed base index with the single *DMU* benchmarking, the fixed base and unit *HMTFP* is specified as:

$$HMTFP_{fb_k} = \frac{D_k^o(y_t, x_k^B) / D_k^o(y_k^B, x_k^B)}{D_k^i(y_k^B, x_t) / D_k^i(y_k^B, x_k^B)} \tag{7}$$

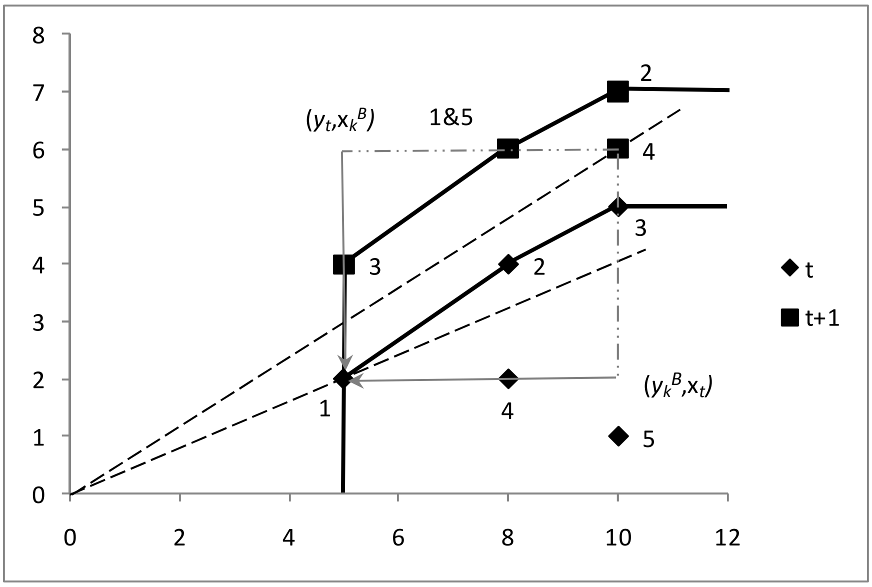
where k is the (constant) base year and t is the year under analysis, (y_t,x_t) are the outputs and inputs of the analyzed *DMU* period t, and (y_k^B,x_k^B) are the outputs and inputs of the unit established as benchmark (fixed in the base year).

Differently from the static case, it is now possible to see movements over time with respect to the *DMU* set as a benchmark. Both the technology frontier and the benchmark are kept fixed in period k. Therefore, by computing changes between period k and period t, $t+1$, etc. one is examining shifts in the technology with respect to a known position set as a goal for the evaluated *DMU*.

Following the previous procedures, by applying expression (7) (see also Figure 2.3) on the example of *DMU* 4, the $HMTFP_{fb}$ is:

$$HMTFP_{fb(DMU4)} = \frac{(6/2)/(2/2)}{(10/5)/(5/5)} = \frac{3}{2} = 1.5 \tag{8}$$

Figure 2.3. Illustration of the Fixed Base *HMTFP* for Benchmarking



Reviewing the distance functions in Figure 2.3, one first observes that the benchmarks' efficient position, (y_k^B, x_k^B)=(2,5), yields values of 1 for this *DMU's* output and input distance functions, $D_k^o(y_k^B, x_k^B)$=(2/2) and $D_k^i(y_k^B, x_k^B)$=(5/5) respectively. Next, (y_t, x_k^B)=(6,5) and (y_k^B, x_t)=(2,10) are fictitious inefficient units in Figure 2.3, defined through combining the output and input of *DMUs* 1 and 4. The arrows in Figure 2.3 show their corresponding distance functions. $D_k^o(y_t, x_k^B)$=(6/2) starts from an output level of 6 and reaches the benchmark's lower output level of 2. Likewise, $D_k^i(y_k^B, x_t)$=(10/5) originates in the input level of 10 and finds the benchmark's input level of 5. The output and input quantity indices linked to the frontier component are found in the numerator and denominator of the $HMTFP_{fb}$. While the output quantity index is (6/2)/(2/2)=3, the input oriented one is (10/5)/(5/5)=2 (columns 5 and 6 in Table 2.1, Panel C). The final result of 3/2=1.5 indicates that the productivity of *DMU* 4 in period *t+1* is 50% better than the productivity of the benchmark in period *t* (column 7 in Table 2.1, Panel C).

Table 2.1. (Panel C)

Adapting the HMTFP to Benchmarking: Numerical Example for the Fixed Base and Dynamic Cases

Period (1)	*DMU* (2)	Output (3)	Input (4)	Fixed base and unit *HMTFP* numer. (5)	Fixed base and unit *HMTFP* denomin. (6)	Fixed base and unit *HMTFP* (7)	Prod. to bench. in base year (Prod DMU in t+1 / Prod Bench t) (8)	*TFP* change to the bench. (*HMTFP* / Bench's *HMTFP*) (9)
t	1 (B)	2	5	-	-	-	-	-
t	2	4	8	-	-	-	-	-
t	3	5	10	-	-	-	-	-
t	4	2	8	-	-	-	-	-
t	5	1	10	-	-	-	-	-
t+1	1 (B)	6	8	3	1.6	1.875	1.875	1
t+1	2	7	10	3.5	2	1.75	1.75	0.76
t+1	3	4	5	2	1	2	2	0.853
t+1	4	6	10	3	2	1.5	1.5	1.28
t+1	5	6	8	3	1.6	1.875	1.875	4

In the one input one output case shown in Table 2.1 (Panel C), the above result is also provided by the productivity of the analyzed *DMU* in *t+1* divided by the productivity of the benchmark in *t* (*i.e., $HMTFP_{fb(DMU4)}$*=0.6/0.4=1.5, see column 8 in Table 2.1, Panel C). This case is illustrated in Figure 2.3 by the dashed lines' slopes: these show that the productivity of the analyzed *DMU* 4 in *t+1* (6/10=0.6) is higher than the productivity of the benchmark unit *DMU* 1 in *t* (2/5=0.4). It can be seen (Table 2.1, Panel C) how all units are better positioned in period *t+1* than their benchmark in *t*. Also, through expression (8), the benchmark's index is showing the movements of this *DMU* among the studied period and the base year. The $HMTFP_{fb(DMU1)}$ (benchmark) is 1.875, which is actually the classical *HMTFP* index result. Moreover, using the $HMTFP_{fb}$ as shown in Table 2.1 (Panel C) and Figure 2.3, the frontier distances can be identified in a clear-cut manner.

The advantage of this second option is the availability of *TFP* changes over time with respect to a benchmark in a base period. However, one could argue against the relevance of the technology at a certain point (the fixed base) and the reality of the period under analysis over time. Since the technology, the evaluated *DMUs* and the benchmark all change over time, the comparison of a *DMU* with regard to a benchmark in a given base year becomes somewhat obsolete after being used for a certain period of time. It is as if one keeps aiming at a target that has meanwhile probably moved onwards.

2.2.3. The Dynamic HMTFP Index for Benchmarking: Decomposing the HMTFP

A third proposal is created from a dynamic viewpoint having as a base the classical *HMTFP* index (see expression (3)). This proposal represents a novelty to the existing literature. The chosen course of action is to decompose the basic *HMTFP* index and adapt its components to dynamic benchmark analysis. Through simple mathematical rearrangement, the *HMTFP* index in expression (3) can be decomposed as follows:

$$HMTFP_t = \frac{D_t^o(y_{t+1},x_t)\,/\,D_t^o(y_t,x_t)}{D_t^i(y_t,x_{t+1})\,/\,D_t^i(y_t,x_t)} =$$

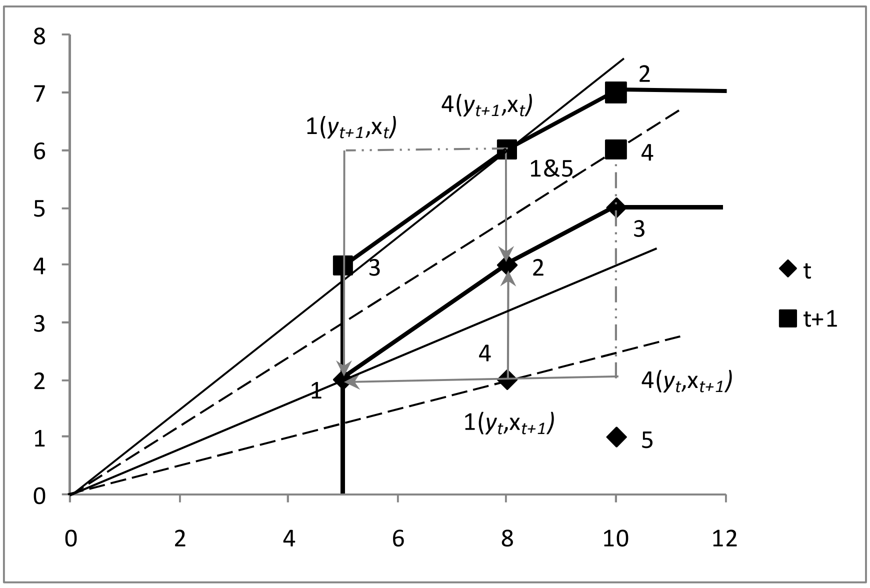
$$= \underbrace{\frac{\dfrac{D_t^o(y_{t+1},x_t)\,/\,D_t^o(y_t,x_t)}{D_t^o(y_{t+1}^B,x_t^B)\,/\,D_t^o(y_t^B,x_t^B)}}{\dfrac{D_t^i(y_t,x_{t+1})\,/\,D_t^i(y_t,x_t)}{D_t^i(y_t^B,x_{t+1}^B)\,/\,D_t^i(y_t^B,x_t^B)}}}_{\substack{\textit{TFP}\text{ change relative to the benchmark (}\textit{i.e.}\text{,}\\ \text{movement across time in the distance from}\\ \text{the unit to the benchmark)}}} \; x \; \underbrace{\frac{D_t^o(y_{t+1}^B,x_t^B)\,/\,D_t^o(y_t^B,x_t^B)}{D_t^i(y_t^B,x_{t+1}^B)\,/\,D_t^i(y_t^B,x_t^B)}}_{\substack{\textit{TFP}\text{ change showing the benchmark's}\\ \text{evolution vis-à-vis the frontier.}}} \qquad (9)$$

where t and $t+1$ are the years under analysis, (y_t,x_t) and (y_{t+1},x_{t+1}) are the outputs and inputs of the analyzed *DMU* in periods t and $t+1$ respectively, and (y_t^B,x_t^B) and (y_{t+1}^B,x_{t+1}^B) are the outputs and inputs of the unit established as benchmark in periods t and $t+1$ respectively.

The dynamic *HMTFP* index together with its benchmarking decomposition offers a twofold perspective. First, the *HMTFP* index shows the *TFP* changes between *t* and *t+1* (see expression (3) and its interpretation). Note that there is no benchmark involved at this point and the analysis maintains the classical changing frontier approach. Consequently, as in expression (3), values higher than 1 show the amount in which a *DMU* improves its *TFP*, while values lower than unity indicate *TFP* decreases (*e.g.,* column 7 in Table 2.1, Panel A shows 1.875 for *DMU* 1, 1.4 for *DMU* 2, etc.).

Next, the decomposition elements introduce the benchmarking perspective. The first index -*TFP* change relative to the benchmark- computes the variation in the distance from the *DMU* under analysis to the benchmark unit. This is simply the division of the *HMTFP* of the analyzed *DMU* to the benchmark's *HMTFP*. For instance, the distance functions computed for *DMU* 4 and its benchmark (*DMU* 1) are given by the arrows in Figure 2.4. These are created in the same manner as the ones explained in relation with expressions (3) and (4).

Figure 2.4. Illustration of the Dynamic *HMTFP* and its Benchmarking Decomposition



In our example, *DMU* 4 has a *HMTFP* index of 2.4 and a *TFP* change relative to the benchmark of 1.28 (column 9 in Table 2.1, Panel C). On the one hand, *DMU* 4's *TFP* growth between the studied periods is captured by the 2.4 result. On the other hand, *DMU* 4's *TFP* growth is shown as higher than the one of the benchmark (*DMU* 1) by the 1.28 score. In contrast, it can be seen how *DMU* 2 (with *DMU* 1 as the benchmark) has a benchmarking score of 0.76. Also, the same *DMU* 2 has a global *HMTFP* index of 1.4. Thus, even if *DMU* 2 improved its *TFP* between periods t and $t+1$, its benchmark had a greater *TFP* increase. Therefore, the result of 0.76 shows the extent to which the benchmark's evolution is superior to the one of *DMU* 2.

Graphically, in the one input one output case, these evolutions are shown by the slopes of the benchmark and those of the analyzed *DMU*. Using Figure 2.4, the evaluation considers the slopes of *DMU* 4 (the dashed lines, (6/10)/(2/8)=2.4) against the equivalent slopes for the objective set as *DMU* 1 (the solid lines, (6/8)/(2/5)=1.875). This result is simply the *HMTFP* of *DMU* 4 (2.4) divided by the benchmarks' *HMTFP* (1.875). This computation follows exactly expression (3) (and the example in expression (4)) and yields the score of 2.4/1.875=1.28. Ultimately, the second decomposition component is a constant value emphasizing the benchmark's *HMTFP* index.

The advantage of the latter approach is that it allows for both the global frontier *TFP* analysis, as well as for the benchmarking approach. Furthermore, by running this decomposition over several consecutive time periods, statistical tests between its components may reveal catching-up effects (respective to the global frontier and/or to the benchmark).

Thus, each of the three adaptations of the *HMTFP* index (expressions (5), (7) and (9)) addresses a certain benchmarking scenario. Naturally, a manager can select the most appropriate method for his/her specific situation and needs. While each of these three approaches can stand alone, these methods are also potentially complementary. In the latter case, a multidimensional picture can be obtained via the parallel interpretations of these three *HMTFP* indices for benchmarking.

3. Description of the Sample

3.1. Description of the Spanish Banking Industry

The Spanish banking industry proves to be attractive for research due to its rapid growth and global competition between different bank types. This growth occurred after the second half of the 1980s, triggered by the deregulation of the sector (Grifell-Tatjé and Lovell 1997b; Cuesta and Orea 2002; Zúñiga-Vicente *et al.* 2004). The year 1989 marks the start of the liberalized Spanish banking market where those earlier viewed as small intermediaries could now act in ways similar to private banks (Zúñiga-Vicente *et al.* 2004). The savings banks benefited most from these policies, since apart from the permission to perform general banking operations they were allowed to expand throughout Spain. Consequently, it was probably the savings banks' strategic choice of expansion that lead to the global competition between private and savings banks still manifest today.

However, the years 1992-1996 represented a crisis in this sector. In 1995, towards the end of this period, a key step for this industry's development was taken through the introduction of a novel legal regime for bank creation. The sector introduced novel technologies (*e.g.*, important increases of *ATMs'* networks, information systems) together with the establishment of new financial products and services (Cuesta and Orea 2002; Zúñiga-Vicente *et al.* 2004). Moreover, at the end of the 1990s the annual reports of the savings banks reveal a clear strategic choice for expansion (mostly through opening new branches). This strong option for growth implies the adaptation of the management of inputs and outputs to new forms of organization. Accordingly, the end of the 1990s represents a cornerstone for growth and is attractive to analyze when developing new lines of research.

Considering the ownership composition, there are three types of banking institutions in Spain: private banks, savings banks, and credit cooperatives. The market belongs with a vast majority to the first two categories, while only 2% of the banking activity remains in the hands of the credit cooperatives (Grifell-Tatjé and Lovell 1997a). The private banks generally pursue the goal of profit maximization. By contrast, the savings banks are public companies, whereas the credit cooperatives frequently belong to their customers. It is important to emphasize two main differences between the credit cooperatives and the other two bank types. First, there are important size dissimilarities as credit cooperatives are a lot smaller. Second, -which may also be an implication of the first- technology is homogenous between the private and savings banks only. The credit cooperatives are less developed not only in terms of branch (geographical) reach, but also in terms of *ATMs* and other products and services.

The above discussion yields two conclusions. First, the analysis' starting point is the year 1998. This corresponds to the end of the financial crisis in a deregulated Spanish banking sector. It also stands for the beginning of a novel growth period defined by new corporate strategies, particularly in the case of savings banks. Second, the homogeneity of the employed technology is guaranteed by forming a sample of private and savings banks (and excluding the credit cooperatives).

3.2. Method of Analysis and Input and Output Variables

Banking studies provide various ways to define the outputs and inputs for productivity and efficiency analyses. Studies reviewing the input and output variables employed in banking are those of Berger and Humphrey (1997) or Goddard *et al.* (2001). There are two main approaches to the choice of how to measure the flow of services provided by financial institutions: these are the production and the intermediation approaches. The production approach considers banks as producers of deposit and loan services. When considering this specification, just physical inputs like labor and capital and their costs must be included. In contrast, the intermediation approach regards banks as intermediaries through which deposits and purchased funds are transformed into loans and financial investments. Hence, under this framework funds and their interest cost (which are the raw material to be transformed) have to be introduced as inputs in the model.

The current contribution selects a traditional production approach having deposits as an output. Following Berger and Humphrey (1997), this study takes into account deposits' output features linked with liquidity, safekeeping and payment services provided to clients. Consequently, inputs are (1) operating assets (defined as total assets – financial assets), (2) labor (number of employees), and (3) other administrative expenses. Outputs are (1) deposits, (2) loans, and (3) fee-generated income (non-traditional output). With the exception of labor, all variables are in monetary terms (thousands of Euros). The reason for this design is quite straightforward. Let us consider two banks having an equal number of deposits, although the monetary quantity in one bank is twice as in the other. In this case, accounting for the deposits in monetary terms is more relevant for showing which bank holds a larger output. Ultimately, labor is used in absolute numbers, as these values prove higher consistency throughout the analyzed sample and produce less bias.

Prior to setting up the final sample, a test for outliers has been performed. It is well-known that extreme points could influence the shape of the estimated production frontier and introduce bias in the *TFP* changes of the entire sample. In relation to frontier analysis, the two most influential contributions are those of Andersen and Petersen's (1993) super-efficiency coefficient and Wilson's (1993) article. Therefore, through the super-efficiency test the influential units found in the sample are removed and the efficiency measure re-estimated. Moreover, following Prior and Surroca (2006), this procedure is continued as long as the null hypotheses of equality between successive efficiency scores cannot be rejected. By doing so, about 6% of the banks in the total sample turn out to be outliers and were therefore eliminated.

In addition, foreign banks that showed inconsistent assets-related information have also been removed. Considering data availability, the calculations are performed on a yearly basis between 1998 and 2006. By balancing the panel corresponding to this period 1998-2006, a final sample of 86 private and savings banks was formed.

Before computing the different specifications of the *HMTFP* indices for benchmarking, the benchmark *DMU* must be selected.[7] As previously mentioned, this choice should be in accordance with each bank's strategic options and competitive positioning. However, for our illustrative purpose, a single benchmark has been established for all banks rather than a specific benchmark per observation. The selection process of this single benchmark took into account two criteria: market share and technical efficiency. Specifically, the benchmark has to be in the top 5 banks in terms of assets, deposits and loans, and had to be technically efficient. The technical efficiency is measured through an output oriented model, assuming a technology with variable returns to scale and strong disposability of inputs and outputs. These criteria were fulfilled by Banco Popular Español (a private bank): see Table 2.2 for the input-output

[7] All computations have been developed in *GAMS*: these routines are available upon request.

levels associated with the benchmark and the sample mean (in the initial, central and final year of the analysis).

Table 2.2. Inputs and Outputs: Benchmark and Mean Sample Levels

			1998	2002	2006
Inputs	**Operating Assets**	**Sector Mean**	364892	727826	891640
		Banco Popular Español	880128	1657076	1904683
	Labor (No. Empl.)	**Sector Mean**	1695	1964	2502
		Banco Popular Español	7312	7856	7864
	Other Adm. Exp.	**Sector Mean**	37139	50469	75204
		Banco Popular Español	102773	146035	164690
Outputs	**Deposits**	**Sector Mean**	3637854	6135306	12705040
		Banco Popular Español	10603669	19412193	39180631
	Loans	**Sector Mean**	2946637	5665585	14877027
		Banco Popular Español	10381559	19977255	42861961
	Fee-Gener. Income	**Sector Mean**	49979	77826	139271
		Banco Popular Español	300668	450797	608480

Note: with the exception of labor which is a physical absolute value, all variables are expressed in monetary terms (thousands of Euros).

The differences indicating the catching-up effects between the analyzed time periods are assessed through a Li test (see Li 1996; Kumar and Russell 2002). This is a non-parametric statistical test for comparing two unknown distributions making use of kernel densities. Its advantages are twofold. First, as stated by Kumar and Russell (2002: 546), the Li test statistic is valid for dependent and as well as for independent variables. Second, in contrast to most statistical tests (*e.g.,* Mann-Whitney, Kolmogorov-Smirnov, Wilcoxon), the Li test is not based on mean or median comparisons, but instead compares two entire distributions against each other. Thus, by means of the Li test p-value, the null hypothesis of equality of distributions can be rejected or not.

4. Empirical Illustration

The interpretation of the results follows the *HMTFP* benchmarking index proposals in Section 2. The first stage of the analysis illustrates each specification's descriptive results together with catching-up effects. Second, the global picture provided by all adaptations of the *HMTFP* index for benchmarking is shown graphically. This second task is undertaken by examining the case of one arbitrarily chosen *DMU*.

Table 2.3 presents the descriptive statistics associated with the $HMTFP_{st}$ and the $HMTFP_{fb}$ indices. The results of the $HMTFP_{st}$ index are straightforward and easy to understand. Considering that the benchmark's score is always equal to 1, all the other values show the distance to this benchmark *DMU*. Keep in mind that results higher than unity indicate better positioning than the benchmark. Therefore, in the static analysis case, all through the years 1998 to 2006, the sample performs better at mean level than the benchmark. The percentiles in Table 2.3 offer more insight into the $HMTFP_{st}$ situation by showing the results' distribution for each period. For instance, in 2005 the sample mean has the value of 1.36 and is therefore 36% better than the benchmark. However, the close to unity median level (see percentile 50) indicates that only half of the *DMUs* are better positioned than the benchmark, while 25% of them are at least 9% (or 1-0.91=0.09) inferior with respect to the same benchmark.

Having the yearly snapshot of the Spanish banking sector in mind, the fixed base benchmark analysis is conducted. The $HMTFP_{fb}$ is computed by taking the initial year (*i.e.,* 1998) as the base frontier and fixing the benchmark in the same period. Generally, this index should be interpreted in the same fashion as its static version. Nonetheless, there are a few differences. It is now important to compare the sample's results against the ones of the benchmark shown in the last column of Table 2.3. Let us take the period 1998-2004 as an example. At mean level, the sample has an outcome of 2.47 in 2004 as compared to the technology and benchmark in 1998. Taking into account that the benchmark's index is 2.33, the difference of 2.47-2.33=0.14 (14%) is in favor of the whole sample. Still, the benchmark's *TFP* is superior to half of the analyzed *DMUs*. At percentile 50, the distance to the benchmark amounts to 2.33-2.22=0.11 (11%).

Table 2.3. Static and Fixed Base *HMTFPs*: Descriptive Statistics

$HMTFP_{st}$	Mean	Std. Dev.	Percentiles					Benchmark's Index
			10	25	50	75	90	
1998	1.4890	0.9015	0.9649	1.1204	1.2397	1.4407	2.5240	1
1999	1.5488	0.8498	1.0176	1.1568	1.3134	1.5900	2.2874	1
2000	1.6000	1.0261	1.0111	1.1321	1.3234	1.5626	2.4131	1
2001	1.9870	2.2991	1.0875	1.3090	1.5372	1.8503	2.3206	1
2002	1.6155	1.1028	1.0248	1.1661	1.3295	1.5838	2.1520	1
2003	1.6050	1.1990	1.0099	1.1441	1.2753	1.5777	2.2222	1
2004	1.5523	1.1856	0.9578	1.0641	1.2168	1.4941	2.5252	1
2005	1.3613	1.0059	0.7560	0.9137	1.0684	1.3366	2.3328	1
2006	1.3360	0.9906	0.7799	0.8675	1.0254	1.3335	2.1380	1
$HMTFP_{fb}$	**Mean**	**Std. Dev.**	**Percentiles**					**Benchmark's Index**
			10	**25**	**50**	**75**	**90**	
1998-1999	1.4600	0.6684	0.9747	1.1498	1.2824	1.4910	2.1705	1.1204
1998-2000	1.6973	1.0059	1.1397	1.2940	1.4248	1.7051	2.3791	1.2836
1998-2001	1.7834	1.2219	1.1229	1.3262	1.5690	1.8320	2.3692	1.4017
1998-2002	1.9733	1.0186	1.3166	1.5234	1.7661	2.0224	2.8444	1.6330
1998-2003	2.1961	1.2713	1.3591	1.6211	1.9238	2.2578	3.0547	1.9976
1998-2004	2.4699	1.3557	1.4999	1.8302	2.2155	2.5992	3.2975	2.3260
1998-2005	2.9945	1.6956	1.7539	2.2626	2.6486	3.1875	4.2854	2.9027
1998-2006	3.4141	1.7020	1.9111	2.6164	3.1989	3.8523	4.6940	3.3308

Further viewpoints on these two benchmarking approaches are given by the Li test. In Table 2.4 the significant catching-up effects between the sample and the benchmark become more obvious. Also, Appendix 2.1 interprets a selection of the Li tests graphically. Each illustration provides the kernel densities of the compared *HMTFP* indices. In this way, one can have a better understanding of when the null hypotheses of equality between the distributions are accepted or rejected. As it can be noticed, the first distribution is represented by a solid line and the second one by a dotted line. In the hypotheses statements below the figures, the first sample is always shown by the solid line.

The $HMTFP_{st}$, for example, shows a widening of the gap between the sample and the benchmark in the year 2001. This gap is then constantly reduced by the benchmark bank during the following years. In contrast, in the base year comparison the scores are regularly significantly increasing compared to the fixed benchmark. The explanation is that while the technology of the analyzed sample is allowed to evolve over time, the benchmark *DMU* and the base technology always remain fixed at their 1998 levels.

Table 2.4. Static and Fixed Base *HMTFPs*: Li Tests for Catching-up Effects

$HMTFP_{st}$	1998	1999	2000	2001	2002	2003	2004	2005
1999	0.320	-	-	-	-	-	-	-
2000	0.286	0.641	-	-	-	-	-	-
2001	0.000***	0.000***	0.000***	-	-	-	-	-
2002	0.129	0.619	0.530	0.002***	-	-	-	-
2003	0.682	0.578	0.433	0.000***	0.306	-	-	-
2004	0.547	0.187	0.263	0.000***	0.027**	0.414	-	-
2005	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	-
2006	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.523
$HMTFP_{fb}$	**1998-1998**	**1998-1999**	**1998-2000**	**1998-2001**	**1998-2002**	**1998-2003**	**1998-2004**	**1998-2005**
1998-2000	-	0.002***	-	-	-	-	-	-
1998-2001	-	0.000***	0.016**	-	-	-	-	-
1998-2002	-	0.000***	0.000***	0.019**	-	-	-	-
1998-2003	-	0.000***	0.000***	0.000***	0.100	-	-	-
1998-2004	-	0.000***	0.000***	0.000***	0.000***	0.003**	-	-
1998-2005	-	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	-
1998-2006	-	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***

*, **, or ***: statistically significant difference at a 90%, 95% or 99% confidence level.

Criticism could regard this comparison as biased. However, the $HMTFP_{fb}$ is related to a component of managerial decision making. Bank leaders may establish as their goal a certain *DMU* in a certain period and try to reach its position through a long term strategy. One the one hand, the difficulties of a changing benchmark are thereby avoided. On the other hand, the interest here is to attain a certain performance a benchmark *DMU* has attained at a specific point in time, and not following that benchmark over time. When the aim is to pursue a benchmark over time, then the traditional dynamic *HMTFP* and its decomposition should be employed.

The classic *HMTFP* index and its decomposition for benchmarking purposes are shown in Tables 2.5 and 2.6. The first *HMTFP* index results are not in relation with any benchmark. These are traditional *TFP* change measures: sample against changing frontier. For example, the mean value of 1.15 in period 2003-2004 indicates a 15% improvement in the use of inputs and outputs in 2004 with respect to *DMUs* and frontier in 2003. These improvements are sustained over the studied period, which is known as an expansion phase for the Spanish banking sector. Also, the positive shifts are greater in the final years (a fact also supported by the test statistics in Table 2.6).

Table 2.5. Dynamic *HMTFP* and Decomposition: Descriptive Statistics

***HMTFP*: Dynamic and Decomposition**		**Mean**	**Std. Dev.**	**Percentiles**				
				10	**25**	**50**	**75**	**90**
1998-1999	***HMTFP***	1.0844	0.1303	0.9635	1.0150	1.0811	1.1191	1.2159
	***HMTFP* to Benchmark**	0.9678	0.1163	0.8599	0.9059	0.9648	0.9988	1.0852
	Benchmark's *HMTFP*	1.1204	Constant value					
1999-2000	***HMTFP***	1.2123	0.3799	1.0172	1.0757	1.1421	1.2037	1.3190
	***HMTFP* to Benchmark**	0.9974	0.3125	0.8369	0.8850	0.9397	0.9904	1.0852
	Benchmark's *HMTFP*	1.2154	Constant value					
2000-2001	***HMTFP***	1.0675	0.3405	0.9021	0.9759	1.0396	1.1155	1.1755
	***HMTFP* to Benchmark**	0.9512	0.3034	0.8039	0.8696	0.9263	0.9940	1.0475
	Benchmark's *HMTFP*	1.1222	Constant value					
2001-2002	***HMTFP***	1.1594	0.1654	0.9946	1.0603	1.1321	1.2236	1.3718
	***HMTFP* to Benchmark**	0.6445	0.6293	0.5529	0.5894	0.6293	0.6802	0.7625
	Benchmark's *HMTFP*	1.7990	Constant value					
2002-2003	***HMTFP***	1.1550	0.2399	0.9933	1.0510	1.0987	1.1889	1.4000
	***HMTFP* to Benchmark**	0.9405	0.1953	0.8089	0.8559	0.8947	0.9682	1.1401
	Benchmark's *HMTFP*	1.2280	Constant value					
2003-2004	***HMTFP***	1.1529	0.1463	0.9976	1.0648	1.1304	1.2151	1.3141
	***HMTFP* to Benchmark**	0.9710	0.1232	0.8402	0.8969	0.9521	1.0235	1.1069
	Benchmark's *HMTFP*	1.1872	Constant value					
2004-2005	***HMTFP***	1.2955	0.3630	1.0385	1.1061	1.1986	1.3506	1.7004
	***HMTFP* to Benchmark**	0.7659	0.2146	0.6140	0.6539	0.7086	0.7985	1.0053
	Benchmark's *HMTFP*	1.6914	Constant value					
2005-2006	***HMTFP***	1.2024	0.2114	1.0469	1.1110	1.1679	1.2403	1.3291
	***HMTFP* to Benchmark**	0.9953	0.1750	0.8666	0.9197	0.9668	1.0267	1.1002
	Benchmark's *HMTFP*	1.2081	Constant value					

Next, the decomposition results lead to competitive advantage interpretations. A straightforward observation is that the second index component (*i.e.,* the benchmark's

HMTFP) always has positive changes. Thus, one can deduce that the comparison is done against a good performing benchmark. However, the attractive component is the *TFP* change with respect to the dynamic frontier and benchmark. Again, the comparison against a fixed unit represents a central issue. This benchmarking procedure measures the changes in the *TFP* of each *DMU* against the changes in the *TFP* of the benchmark. In most of the analyzed years, these changes (at mean and median levels) are inferior to the ones of the benchmark.

Table 2.6. Dynamic *HMTFP* and Decomposition: Li Tests for Catching-up Effects

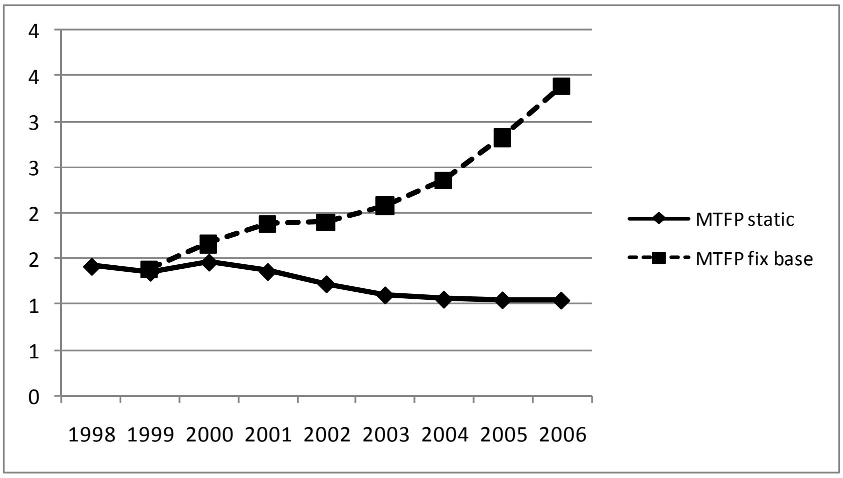
***HMTFP* (Classic)**	**1998-1999**	**1999-2000**	**2000-2001**	**2001-2002**	**2002-2003**	**2003-2004**	**2004-2005**
1999-2000	0.009***	-	-	-	-	-	-
2000-2001	0.044**	0.000***	-	-	-	-	-
2001-2002	0.000***	0.500	0.000***	-	-	-	-
2002-2003	0.280	0.130	0.007***	0.141	-	-	-
2003-2004	0.020**	0.791	0.000***	0.725	0.170	-	-
2004-2005	0.000***	0.085*	0.000***	0.302	0.000***	0.172	-
2005-2006	0.000***	0.232	0.000***	0.122	0.000***	0.203	0.007***
***HMTFP* to Benchmark**	**1998-1999**	**1999-2000**	**2000-2001**	**2001-2002**	**2002-2003**	**2003-2004**	**2004-2005**
1999-2000	0.001***	-	-	-	-	-	-
2000-2001	0.036**	0.725	-	-	-	-	-
2001-2002	0.000***	0.000***	0.000***	-	-	-	-
2002-2003	0.000***	0.009***	0.036**	0.000***	-	-	-
2003-2004	0.126	0.513	0.611	0.000***	0.000***	-	-
2004-2005	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	-
2005-2006	0.707	0.098*	0.140	0.000***	0.000***	0.587	0.000***

*, **, or ***: statistically significant difference at a 90%, 95% or 99% confidence level.

At the beginning of the analyzed period, the sector mean and the benchmark maintain a close relation in terms of *TFP* changes. Nevertheless, shifts appear over time and the distances increase in specific periods such as 2004-2005 (in this period the benchmark experiences changes higher than almost 90% of *DMUs*). This lag is then reduced during the next two-year span, when the "normality" of 50%-70% *DMUs* below the benchmark value is reestablished (see test statistics in Table 2.6). A similar situation is also present earlier in the studied period. The benchmark moved away from the industry mean in 2001-2002 and was consequently caught-up to in 2002-2003.

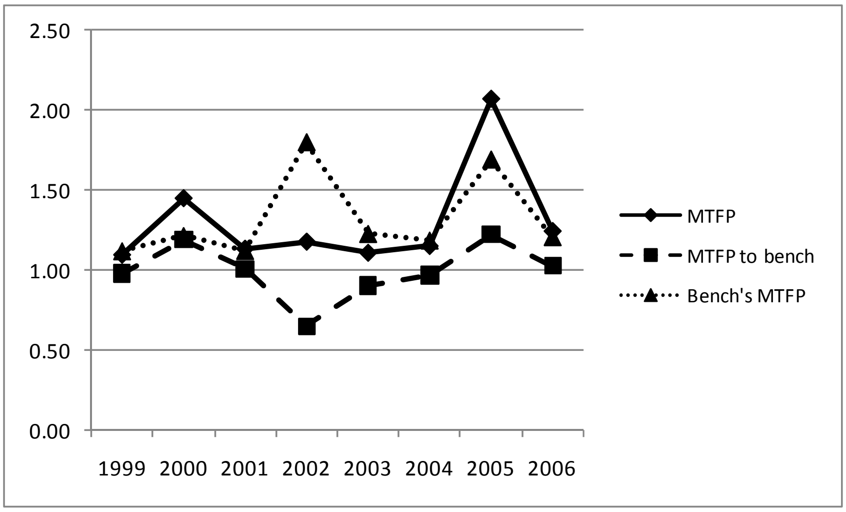
After progressively advancing into the *TFP*-benchmark analysis of the Spanish banking sector, the proposed methodology can now present a global picture by combining the three approaches. As mentioned before, these independent benchmarking measures can be combined to achieve potential complementarities. To exemplify this type of analysis, the *DMU* Bilbao Banco Vizcaya Argentaria (*BBVA*) has been arbitrarily chosen from the sample, while the benchmark continues being Banco Popular Español. Figures 2.5 and 2.6 demonstrate graphically how all three approaches evolve through time.

Figure 2.5. Static and Fixed Base *HMTFPs* – The Case of Banco Bilbao Vizcaya Argentaria (BBVA)



This *DMU's* evolution can be compared to the above mean values per sector and benchmarking approach. In Figure 2.5, the $HMTFP_{st}$ and $HMTFP_{fb}$ indices illustrate the evaluations from the viewpoint of unchanging technologies. The former shows quite constant results, as even if stable in each period, the technology is allowed to change in each year together with the sample. The latter indicates a positive growing trend throughout the analyzed period, thus pointing towards the technological progress of the Spanish banking. The industry's overall progression can also be seen in Figure 2.6 by means of the *HMTFP* index and its components. It is essential that a bank manager (or of any other firm in a different industry for that matter) is able to see at the end of the analysis different *TFP* changes and/or benchmarking aspects of the analyzed *DMU*.

Figure 2.6. Dynamic *HMTFP* and its Benchmarking Decomposition – The Case of Banco Bilbao Vizcaya Argentaria (BBVA)



5. Concluding Remarks

This research is founded in the traditional view of benchmarking as the search and emulation of best practices. By applying the *HMTFP* index (Bjurek 1996), this study aims at closing the gap between benchmarking and multi inputs and outputs *TFP* frontier analysis. In this way, *TFP* benchmarking can be a new way of setting strategic objectives and analyzing firm performance.

Each organization can opt for its own preferred scenario for benchmarking, involving the selection of either an efficient or an inefficient benchmark. First, comparisons can be made against efficient companies. This approach reveals if the firm has a best or worst position in the market and the eventual distance that separates it from the efficient position. This is also a method to discover, understand and implement new organizational practices. Second, benchmarking can be done by selecting an inefficient but strategically attractive firm as a target. In this case the benchmark can simply be a local competitor (or any other firm for that matter). Additionally, both settings provide information linked to the efficiency frontier and contribute to organizational learning and strategic planning.

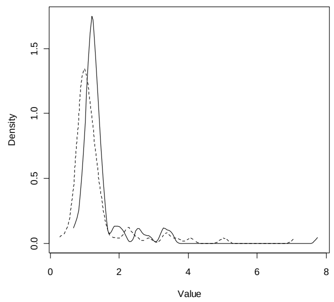
The advantages of the proposed tool for benchmarking are various. First, this Hicks-Moorsteen type index, which is rather scarcely used, solves known problems of *TFP* measurement in the presence of variable returns to scale. Furthermore, under weak assumptions, this index does not lead to infeasible results. This property is crucial for benchmark analysis as specific results per firm have to be provided. Thus, an initial implication could be that the *HMTFP* index deserves greater attention.

Second, through straightforward manipulations of the *HMTFP* index, a versatile tool for benchmarking analysis has been obtained. Pursuing a global image of *TFP* benchmarking, three measures result from diverse assumptions: (1) static benchmark analysis, (2) fixed base and unit benchmark analysis, and (3) dynamic analysis and benchmarking decomposition. These viewpoints assume fixed *DMUs* as benchmarks (very little used in previous analyses) and/or base technologies (the classical benchmark approach) together with the pros of the standard *HMTFP* index. As stated before, each of these settings enables the manager to see a certain facet of the firm's activity. While these benchmarking indices are stand alone tools, they can also be potentially combined to offer a broader perspective for decision making. Furthermore, these methodological tools, here illustrated for the Spanish banking sector, can be applied to any industry.

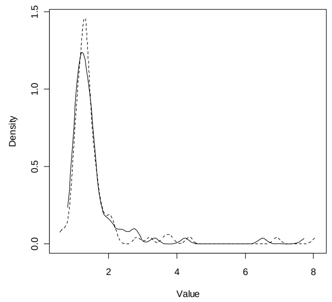
This paper used benchmark selection criteria based on general characteristics (*i.e.,* market share and technical efficiency). However, each *DMU* can establish its benchmark as a function of its own criteria: strategic group membership, environmental variables, ... to name just a few of the options.

An attractive future line of research is linked with the benchmark selection method. It could be interesting to define analyses by benchmarking against strategic groups' leaders or simply considering the regional competitor and to see how these different options affect the performance of firms over time.

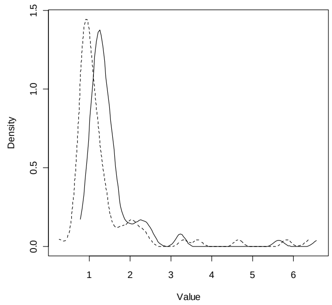
Appendix 2.1. Catching-up Tests between Distributions: Li Test (selection)



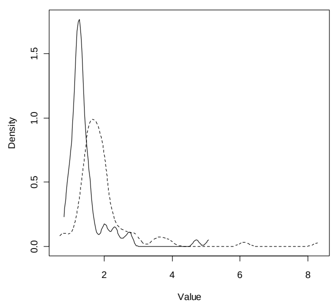
$HMTFP_{st}$ 98⇔01 H_0 rejected



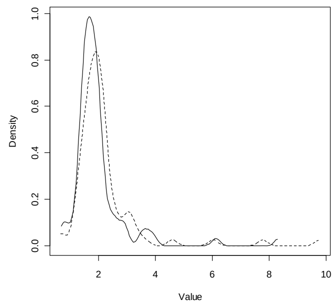
$HMTFP_{st}$ 00⇔02 H_0 accepted



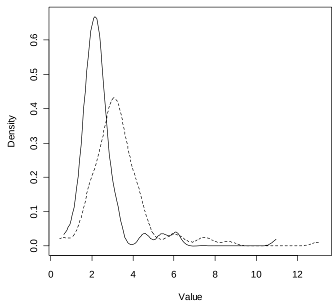
$HMTFP_{st}$ 99⇔06 H_0 rejected



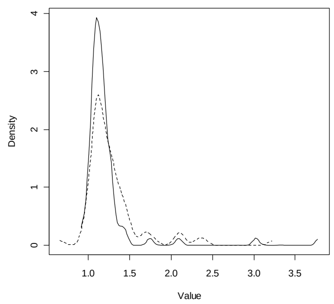
$HMTFP_{fb}$ 98-99⇔98-02 H_0 rejected



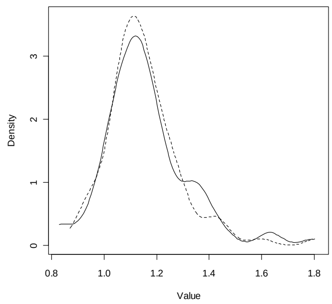
$HMTFP_{fb}$ 98-02⇔98-03 H_0 accepted



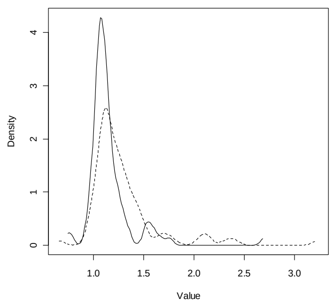
$HMTFP_{fb}$ 98-04⇔98-06 H_0 rejected



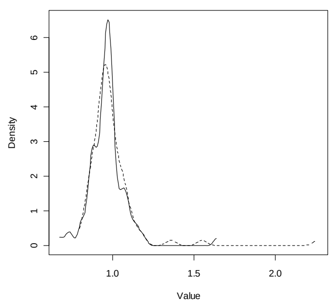
HMTFP 99-00⇔04-05 H_0 rejected



HMTFP 01-02⇔03-04 H_0 accepted



HMTFP 02-03⇔04-05 H_0 rejected



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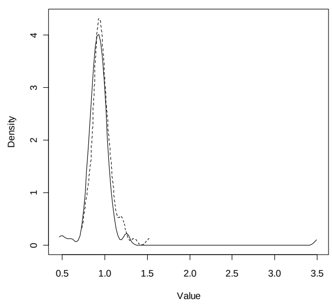

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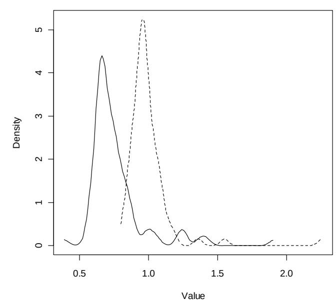


$HMTFP_{to\_bench}$ 04-05⇔05-06 H_0 rejected

Chapter 3:

Revealing Efficiency Gains from Mergers:

Convex vs. Non-Convex Technologies

Abstract

Existing efficiency studies of mergers and acquisitions assess the potential post-merger benefits and often found few significant results. We speculate that this is partly attributable to methodological assumptions. In particular, the assumption of a convex technology frontier can be an important influence on the results obtained. Thus, this contribution uses both convex and non-convex technologies to reveal post-merger cost gains due to scale and technical inefficiencies. These are reported as cost excesses, an aspect which provides proximity to the managerial community. Furthermore, ex ante conditions for achieving potential cost reductions are tested via the ex post examination of the results. The analyzed sample consists of 32 mergers and acquisitions that occurred in the Spanish banking industry between 1988 and 2006. First, it is found that the non-convex estimations are closer to the movements in the observed costs. Second, significant cost excess reductions caused by decreases in scale and technical inefficiencies appear two years after the merger event. Also, it is shown how the non-convex measures are able to illustrate the positive outcomes of mergers, minimizing the risk of undervaluation. The proposed methodology is of interest for future research, since the recent crisis may induce a new wave of financial consolidation.

Keywords: Mergers and Acquisitions, Cost Inefficiency, Scale Economies, (Non)-Convexity, Spanish Banking Industry.

1. Introduction

The literature offers surveys on the effect of the mergers and acquisitions (*M&As*) of banking units from various viewpoints (see Berger *et al.* (1999), Amel *et al.* (2004) and DeYoung *et al.* (2009)). Even if consensus exists on the forces driving the *M&As* in the financial industry, the results on possible efficiency gains remain in general inconclusive. The above mentioned surveys do not allow to deduce that there is a clear conclusion on whether *M&As* improve bank efficiency or if merged banks are more efficient than non-merged ones. Some of the existing studies find positive efficiency effects of *M&As*, while many others find little or non-significant changes. One can speculate that the choice of theoretical assumptions could play a role in this lack of ex post findings. A common aspect of most of the previous research is the employment of convex technologies when computing efficiency measures. Thus, it may be useful for new proposals to consider utilizing non-convex technologies and cost functions (see Briec *et al.* 2004).

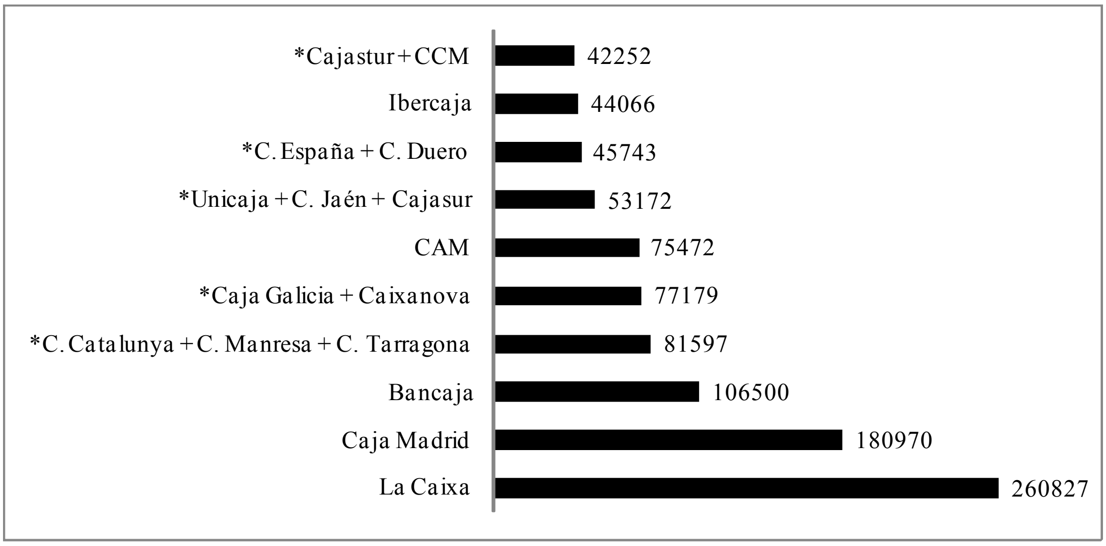
The use of efficiency frontiers for *M&As'* analyses has been a frequent practice in the past literature (see, *e.g.*, Berger *et al.* 1999). When performing multi-objective examinations of technical or cost efficiency frontiers, one has two main alternatives. These either assume a convex technology (*i.e.* Data Envelopment Analysis (*DEA*)) or a non-convex technology (*i.e.* Free Disposal Hull (*FDH*)) (see Ray (2004) for theoretical specifications). The convex method is by far more popular and can be encountered in the majority of frontier applications. Nonetheless, non-convex frontiers offer more accurate inner approximations of the true technology (Briec *et al.* 2004). Practically, one finds that in *DEA* the inefficiency is always higher than, or equal to, the one in *FDH*. This implies that potential post-*M&As* gains expressed as a convex frontier target are sometimes too hard to attain, being an over-optimistic (or demanding) goal. In the context of *M&As* this dissimilarity in pursued inefficiency reductions is crucial for the activity planning and its assessment. Therefore, this empirical analysis takes into account both convex and non-convex technologies and illustrates the differences between the two.

The gains are revealed with respect to two of the *M&As* key objectives: reductions of existing cost excess due to scale and technical inefficiencies. Rather than reporting in terms of relative inefficiencies, results are shown as monetary excesses. This provides proximity to the managerial community, which generally evaluates inefficiencies in terms of cost excess instead of ratios. One can hypothesize that by merging banks create cost excess, which represents room for future improvements. Specifically, with respect to the pre-merger frontier, the cost excess of the potential merger tends to be higher than the ex ante cost excesses of the merging banks. This larger excess favors additional cost cuts which can be accomplished through efficient post-*M&As* managerial practices. Accordingly, even when local inefficiencies are under control, *M&As* can be sources of cost-related gains due to potential economies related to both the scale and technical efficiency components. Linked to this, prior research suggests the need to study various ex post periods (generally two to three years) to reveal significant inefficiency reductions (see, *e.g.*, DeYoung *et al.* 2009).

M&As in the banking sector are a current topic of interest for the Spanish economy. Against the background of the recent financial crisis, policies from the Spanish central bank indicate the need of consolidation via *M&As*. This reorganization of the sector is principally designed for savings banks. Among others, the objectives stated by the Spanish central bank include providing more safety to bank operations through attaining bigger size and bigger equity, and consequently a better control of operating risks. From the viewpoint of the central institution, the consolidation may well be seen as a way of improving bank efficiency by optimizing the networks of branches and clean-ups of toxic assets.

This subject was extensively covered by the national press. For instance, in view of the new *M&As* wave, the finance oriented Spanish journal *Capital*, published in January 2010 the future ranking of savings banks (see Figure 3.1). It can be noticed that no less than five *M&As* would change the configuration of the savings banks' top ten in terms of total assets. Hence, novel proposals should be prepared to scrutinize their prospective gains once there are sufficient ex post periods to analyze. For the time being, these proposals can be tested against the existing *M&As*.

Figure 3.1. Spanish Savings Banks: A New Ranking



*: Planned mergers, as announced in 2009.
Values indicate the total amount of assets in millions of Euros.

The previous wave of *M&As* in the industry was triggered by the deregulation process at the end of the 1980s, beginning of the 1990s. Moreover, the post-deregulation period was characterized by enhanced levels of competition and growth. Due to these facts, vast amounts of research have looked at the efficiency Spanish banks' *M&As* (see, *e.g.*, Grifell-Tatjé and Lovell 1996, 1997b; Lozano-Vivas 1998; Cuesta and Orea 2002; Carbó-Valverde and Humphrey 2004; Crespí *et al.* 2004). Yet, as before mentioned, on many occasions the efficiency results were unclear. These findings are in line with the international surveys on banking *M&As* (see, *e.g.*, Berger *et al.* 1999). For instance, Grifell-Tatjé and Lovell (1996, 1997b) and Lozano-Vivas (1998) find no gains from *M&As*, while Cuesta and Orea (2002) show increases in the post-*M&As* efficiency levels. Thus, it may be interesting to re-assess some of these previous merger events in view of the upcoming *M&As*.

This study uses both convex and non-convex technologies to investigate the cost excess gains from 32 *M&As* that occurred during 1988-2006 in the Spanish banking industry. In particular, ex ante conditions are constructed for predicting the expected reductions in cost. These are then tested by ex post analyses, which demonstrate the attained significant improvements. Additionally, the difference between the two types of efficiency measures (*i.e.* convex and non-convex) and their utility are emphasized throughout the interpretation of empirical results.

This study is structured in six sections. Section 2 offers a brief literature review on the efficiency of *M&As* in the banking industry. Section 3 introduces the methodology utilized and the proposal for ex ante and ex post analyses. Sample-related information and the description of the variables are in Section 4. Section 5 contains the empirical results and their interpretation. The final section formulates key conclusions and suggests directions for future research.

2. Efficiency Gains from *M&As* in Banking: Brief Literature Overview

2.1. Causes and Effects of M&As

Literature proposes various viewpoints on why and how to study the efficiency of *M&As* in the financial sector. To identify the key elements to be analyzed, one can refer to the comprehensive reviews of Berger *et al.* (1999) (over 250 references), Amel *et al.*

(2004) (covers most industrialized countries and financial industries) and DeYoung *et al.* (2009) (over 150 post-2000 studies). According to Berger *et al.* (1999), there are two main types of causes for *M&As*, involving either (1) value maximization motives or (2) non value maximization motives.

The first category includes pursuing increases in efficiency and market share or simply increases in assets' value to reach government safety nets. With respect to the non value maximization, the presented approaches consider the role of managers' own objectives (*i.e.* utility maximization) and the influence of regulations. It can be noted that two motives that are present in different cases (*i.e.* reaching safety nets and the role of regulations) are crucial in the context of financial instability. Furthermore, for the post-2000 period, the same non value maximization motives are highlighted by DeYoung *et al.* (2009). To the two mentioned causes, DeYoung *et al.* (2009) add systemic risk. This is the fear that system-wide distress may be produced by the insolvency of one large or important institution.

Apart from the above major motives, a series of additional factors stimulated the accelerated pace of the *M&As*' phenomenon at the end of the 1990s. Past research highlighted (for both the US and Europe) the importance of technological progress, improvements of financial conditions, accumulation of excess capacity, international consolidation of markets and deregulation of geographical or product restrictions (Berger *et al.* 1999; Amel *et al.* 2004).

Thus, a wide variety of efficiency oriented studies mostly employed frontier methods (*i.e.* technical, cost or profit efficiency measures) to compute gains from *M&As*. These gains are generally revealed in terms of a scale, scope or mix of output that is more profitable (Berger *et al.* 1999). Appendix 3.1 provides a brief overview of the literature on the efficiency of *M&As*.

On the one hand, in the case of basic *DEA* models, the analysis requires less information, as no input or output prices are needed. In this case, the results are interpreted in terms of managerial practices and are rather inconclusive throughout the literature with respect to post-*M&As* efficiency gains. For instance, Avkiran (1999) finds by means of *DEA* that the acquiring banks' pre-*M&As* technical efficiency is not always maintained. This is consistent with similar studies, which do not necessarily encounter positive efficiency effects of mergers (Avkiran 1999; Berger *et al.* 1999).

On the other hand, cost or profit functions include other dimensions of the evaluated *M&As*, as they employ data on costs and prices. Even so, many of the results remain unclear. Profit efficiency can be higher for big banks (Berger *et al.* 1993), higher for small banks (Berger and Mester 1997) or equal between the two types (Berger *et al.* 1999). There are, however, two US studies of *M&As* which (via dynamic methods) find improved post-merger profit efficiency (Akhavein *et al.* 1997; Berger 1998). Moreover, Akhavein *et al.* (1997) encounter this positive impact simultaneously with little changes in cost efficiency.

The latter result is consistent with the survey of Berger *et al.* (1999), which shows little or no improvement in the post-merger cost efficiency of US institutions (5% or less). However, many European studies show positive outcomes from *M&As* (DeYoung *et al.* 2009). To review these findings one can refer to recent evidence from Spain (De Guevara *et al.* 2005; De Guevara and Maudos 2007), Norway (Humphrey and Vale 2004) or Germany (Koetter 2005). Additionally, an international (European) study attained results opposite to Akhavein *et al.* (1997). As indicated by DeYoung *et al.* (2009), Huizinga *et al.* (2001) put forth cost efficiency gains together with relatively small profit efficiency enhancements. A common point of these studies is the need for various years (up to seven for the German sample) for the gains to appear.

Motives for cost efficiency studies are also identified by Amel *et al.* (2004). They indicate that, for both the US and Europe, banks operate on average at 10% to 25% of cost inefficiency. Therefore, pre-*M&As* cost inefficiency can be used as an ex ante condition for merger events, which in turn can be regarded as solutions for reducing this inefficiency. Results seem to be dissimilar between the mergers of equals and the *M&As* in which the acquiring unit was more efficient than the acquired one (Berger *et al.* 1999; Amel *et al.* 2004). For example, significant efficiency gains are predicted by the studies of Akhavein *et al.* (1997) and Berger (1998) for situations in which the participating banks were less efficient than their peers prior to the merger event.

Furthermore, these results were equally valid for cost and profit efficiencies and for *M&As* among large or small institutions (Berger *et al.* 1999; Amel *et al.* 2004). Linked to this, Amel *et al.* (2004) determine that the common *M&As* in the European context mostly involve efficient banks that acquire institutions with worse performance. What is more, in Europe size does not seem to matter for obtaining scale economies (Altunbas *et al.* 2001). Nevertheless, efficiency gains from exploiting scale economies stop once a certain size is reached (Altunbas *et al.* 2001).

2.2. The Efficiency of Mergers and Acquisitions in the Spanish Banking Sector

Consensus exists in the literature on the issue that deregulation processes highly enhance the *M&As*-related activity (Grifell-Tatjé and Lovell 1997b; Avkiran 1999; Berger *et al.* 1999; Glass and McKillop 2000; Cuesta and Orea 2002). This is the background of most of the research on *M&As* conducted within the Spanish banking sector. In fact, the deregulation that occurred in this industry at the end of the 1980s made way for important *M&As*. However, the results of previous studies on these Spanish banking *M&As* were rather inconclusive.

For instance, Grifell-Tatjé and Lovell (1996) report no productivity gains from *M&As* between savings banks. Later on, Grifell-Tatjé and Lovell (1997b) split the savings banks into one group that participated in *M&As* and one that did not, and find the values of technical efficiency between the two samples to be similar. Although, Lozano-Vivas (1998) uses the whole sample for the analysis, the results show no significant cost reduction from *M&As* between private or savings banks. Carbó-Valverde *et al.* (2003) report no impacts on efficiency from *M&As* between savings banks, as their costs increased at the same pace as the industry average.

By contrast, Carbó-Valverde and Humphrey (2004) find that *M&As* involving savings banks reduce cost and improve resource allocation, but not by much. A more significant result is that the probability of success is higher in the case of large *M&As* (scale effect) and for *M&As* concerning previously merged banks (learning effect) (Carbó-Valverde and Humphrey 2004). The same *M&As* of savings banks are analyzed in Bernad-Mocate *et al.* (2009): these authors conclude that only one third of the cases have positive evolutions in both productivity and profitability, while many others do not improve even in the long run.

More consistent results can be encountered in Cuesta and Orea (2002) who identify different patterns of development for merged and non-merged firms. Starting off at the same point, the merged units show an initial decrease in technical efficiency followed by increases which indicate that the merged banks are more efficient than the non-merged ones (Cuesta and Orea 2002). The limitation is that the largest savings banks that merged in the early 1990s are less efficient than non-merged banks (Cuesta and Orea 2002; Han *et al.* 2005). Otherwise, positive aspects of the Spanish banking *M&As* are related to capacity efficiency. Enhancements in capacity efficiency are found in connection with the early 1990s merger wave (Prior 2003). These were achieved through branch network adjustments and reallocation of invested physical capital, thus indicating the possibilities of merger activities (Prior 2003).

M&As also appear as methods of government intervention, mostly regarding savings banks, and generally have a positive effect on performance (Crespí *et al.* 2004). The same authors state that for better using *M&As* as a disciplinary tool, the sector should be further deregulated to permit savings banks from different regions to merge.

Still, there are a couple of limitations to the above research. First, some of the studies have one drawback related to the short post-*M&As* period analyzed (*e.g.* Grifell-Tatjé and Lovell 1996; Lozano-Vivas 1998). Bear in mind that this was identified as a central element for observing *M&As*-related gains by Berger *et al.* (1999) and DeYoung *et al.* (2009), for both the US and Europe. Hence, it is advisable to re-examine some of the Spanish banking *M&As*' effects using longer time periods.

Second, a common aspect of the literature on *M&As* is the use of convex technologies for the computation of technical or cost efficiency scores. We speculate that this convexity assumption may be the source of some of the unconclusive outcomes. Consequently, it is useful to re-assess some existing studies using non-convex technologies and cost functions (see Briec *et al.* 2004).

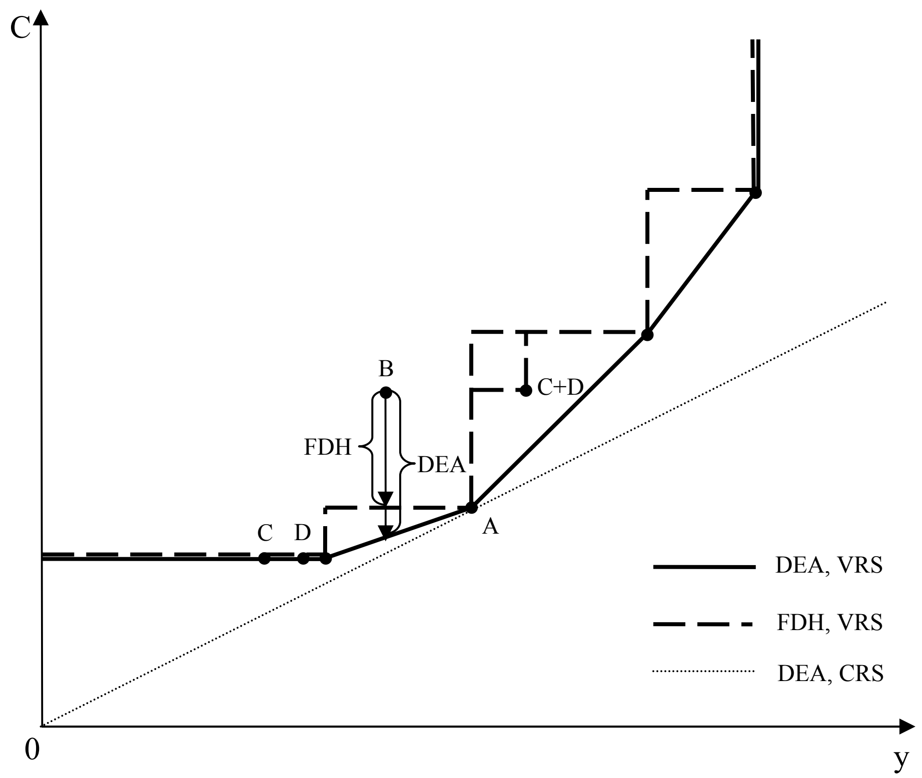
The following section describes the proposed efficiency measurement methods. First, these are designed to build on previous research and provide ex ante conditions together with ex post measures of potential efficiency gains from *M&As*. Second, these take into account the discussed convexity assumption. Via comparisons between convex and non-convex technologies, one can illustrate the differences in efficiency measures and more accurately reveal the gains from *M&As*.

3. Models to Evaluate Gains from M&As: Convex vs. Non-Convex Technologies

3.1. DEA and FDH as Measures of Gains from M&As

As previously indicated, most efficiency studies employ convex methods to assess the gains from mergers. These are usually defined under the framework of *DEA* technical, cost or profit efficiencies. Nevertheless, even if on rare occasions, research on *M&As* relaxed the convexity assumption, using the *FDH* specification (*e.g.* Bogetoft and Wang 2005)[8].

Figure 3.2. Convex vs. Non-Convex Cost Efficiency Frontiers



Both *DEA* and *FDH* act in multi-objective contexts and are based on approximations of true but unknown technology frontiers. They are attractive because they can act in non-parametric environments with no a priori restrictions on the mathematical formula for a specific production function or a specific distribution

[8] One can refer to Ray (2004) for detailed descriptions of *DEA* and *FDH*.

assumption for the residuals. Albeit less popular, the *FDH* (see Deprins *et al.* 1984; Tulkens, 1993) provides a more precise inner approximation of the true, strongly disposable technology (Färe and Li 1998; Briec *et al.* 2004). The main contribution of Deprins *et al.* (1984) was to relax the convexity assumption in *DEA*. Therefore, in the *FDH* definition the activity variables are binaries, whereas the *DEA* efficiency frontier represents linear combinations of observed production plans. More importantly, the *FDH* has the advantage of providing real *DMUs* from the sample as efficient benchmarks (in contrast to *DEA* which may also recommend fictitious projections).

For a better understanding, Figure 3.2 illustrates the efficiency frontiers corresponding to the *DEA* and *FDH* technologies. This is done in a cost efficiency context assuming variable returns to scale (*VRS*). The vertical axis depicts the total cost (C) and the horizontal one represents the output level (y).

The two cost efficiency measures can be interpreted using the Decision Making Units (*DMUs*) A and B. It is easily noted how the *FDH* frontier is closer to the true technology, embodied by the actual *DMUs* under analysis. For that reason, the inefficiency in *DEA* is always higher than (in the case of *DMU* B), or equal to (for *DMU* A), the one in *FDH*. This is straightforwardly illustrated by the arrows linked to *DMU* B's efficiency measures. The cost *DMU* B has to reduce to reach the *FDH* efficiency frontier is smaller than the one required by the *DEA* efficiency frontier. Moreover, the projection of *DMU* B on the convex frontier does not offer a unique benchmark. This is not the case of the *FDH* model, which finds *DMU* A (*i.e.* a *DMU* in the analyzed sample) as the efficient benchmark for *DMU* B.

Apart from the efficiency of *DMUs* A and B, Figure 3.2 also shows the efficiency of the hypothetical merger *DMU* C+D. The two merging *DMUs* C and D are efficient with respect to both *DEA* and *FDH* frontiers. However, after the merger, the newly created *DMU* C+D is efficient only in the new *FDH* frontier, while it is inefficient in the old convex *DEA*. Accordingly, in *DEA* one expects to find fewer gains from *M&As* compared to *FDH*, which is exactly the point one would like to illustrate empirically.

Potential gains from *M&As* are fewer in *DEA* due to the fact that their corresponding total cost is smaller. Nevertheless, this relationship also implies that more possible future gains can be achieved. These assumptions are further explained and illustrated in Subsection 3.3. The problem at hand is to scrutinize to what extent these gains are achievable. It is obvious that they depend on the technology representation, putting more weight on the importance of method selection. Finally, one should be aware that from a manager's perspective no frontier comparison is needed. Managerial communities only compare average observed costs pre- and post-merger event. Consequently, an appropriate specification is the one that best combines the managerial approach with the frontier computations.

The next subsection defines the mathematical formulations corresponding to both *DEA* and *FDH* cost efficiencies. This is done by equally considering relative and monetary terms. Furthermore, the measures are developed assuming variable or constant returns to scale (*VRS* or *CRS*) to allow for the computation of scale efficiency.

3.2. Convex and Non-Convex Cost Efficiency Measures: Definitions and Interpretations

Let $\mathbf{x} = (x_1, \ldots, x_n) \in R_+^n$ and $\mathbf{y} = (y_1, \ldots, y_m) \in R_+^m$ be the vectors of inputs and outputs, respectively, and define the technology by the set *T*, which represents the set of all output vectors (**y**) that can be produced using the input vector (**x**):

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

Following Ray (2004: 214), one can define cost minimization in the subsequent way. Given an input price vector w^0 and assuming *VRS*, the minimum cost is:

$$C^* = \min w^0 x \tag{2}$$

A *DEA* cost minimization linear programming (*LP*) problem can be solved by:

$$\begin{aligned}
&\min \sum_{i=1}^{n} w_i^0 x_i \\
&\text{s.t.} \\
&\text{(a): } \sum_{i=1}^{n} \lambda_j x_{ij} \le x_i \ \ (i = 1, 2, \ldots, n); \\
&\text{(b): } \sum_{i=1}^{n} \lambda_j y_{rj} \ge y_{r0} \ \ (r = 1, 2, \ldots, m); \\
&\text{(c): } \sum_{i=1}^{n} \lambda_j = 1; \\
&\text{(d): } \lambda_j \ge 0 \ \ (j = 1, 2, \ldots, N).
\end{aligned} \tag{3}$$

The assumption of *VRS* in the *DEA* problem introduced by equation (3) can be changed to *CRS* by simply removing restriction (c) related to the activity vector *λ*.

Additionally, the same equation can be the basis of the *FDH* cost minimization problem, through which the non-convex efficiency frontier can be shaped when assuming *VRS*. In this case, one should redefine the restriction (d) of equation (3):

$$\begin{aligned}
&\min \sum_{i=1}^{n} w_i^0 x_i \\
&\text{s.t.} \\
&\text{(a): } \sum_{i=1}^{n} \lambda_j x_{ij} \le x_i \ \ (i = 1, 2, \ldots, n); \\
&\text{(b): } \sum_{i=1}^{n} \lambda_j y_{rj} \ge y_{r0} \ \ (r = 1, 2, \ldots, m); \\
&\text{(c): } \sum_{i=1}^{n} \lambda_j = 1; \\
&\text{(d): } \lambda_j \in \{0, 1\} \ \ (j = 1, 2, \ldots, N).
\end{aligned} \tag{4}$$

Observe, in equation (4) how the activity vector λ in restriction (d) is now limited to be a binary variable to allow constructing a non-convex frontier.

The definition of an *FDH* cost minimization model assuming *CRS* is more complex than in the *DEA* case. Its formulation can be introduced adapting equation (4) to the model proposed by Kerstens and Vanden Eeckaut (1999: 212):

$$\min \sum_{i=1}^{n} w_i^0 x_i$$

s.t.

$$\begin{aligned}
&\text{(a)}: \sum_{i=1}^{n} v_j x_{ij} \leq x_i \ \ (i = 1, 2, \ldots, n);\\
&\text{(b)}: \sum_{i=1}^{n} v_j y_{rj} \geq y_{r0} \ \ (r = 1, 2, \ldots, m);\\
&\text{(c)}: \sum_{i=1}^{n} \lambda_j = 1;\\
&\text{(d)}: \lambda_j \in \{0,1\} \ \ (j = 1, 2, \ldots, N)\\
&\text{(e)}: v_j = \delta\lambda_j, \ \ \delta \geq 0.
\end{aligned} \tag{5}$$

As stated by Kerstens and Vanden Eeckaut (1999: 212), "there is now one activity vector λ operating subject to a non-convexity constraint and one rescaled activity vector v allowing for any scaling of the observations spanning the frontier. The scaling parameter (δ) is free".

In Figure 3.3, one can see how the cost inefficiencies differ between the various types of frontier specifications, fact due to their theoretical underpinnings. For instance, for *DMU* (A+B) it can be noticed how the inefficiency in *DEA CRS* is larger than the one in *DEA VRS*, which in turn is superior to the *FDH VRS* one. Still, as a common point between all the above problems, a *DMU* is identified as being cost efficient when its optimal frontier cost (C^*) is equal to its observed cost (C^O). Bear in mind that while the observed cost (C^O) is equal between all specifications, the frontier cost (C^*) is computed and therefore can be different for each of them. The cost efficiency of the firm can be defined as:

$$C_{eff} = \frac{C^*}{C^o} \leq 1. \tag{6}$$

Consequently, the degree of inefficiency is given by 1-C_{eff}, showing in relative terms the percentage of cost reduction needed to reach the cost efficiency frontier.

Alternatively, one can compute (in monetary terms) the cost excess (C_{excess}) as the difference between the observed cost (C^O) and the frontier cost (C^*):

$$C_{excess} = C_O - C^* \geq 0. \tag{7}$$

A firm has no cost excess (and is cost efficient) when C_{excess} = 0. Values higher than 0 show the amount of cost that should be reduced in order to be efficient.

Thus, while both cost efficiency (C_{eff}) and cost excess (C_{excess}) measure the outcome via the same variables, their interpretation is different. Generally, the management and accounting communities are accustomed to evaluate differences (expressed in monetary terms) rather than ratios. Moreover, they usually utilize differences in observed costs (C^O), without taking into account the concept of frontier efficiency and frontier costs (C^*). Ratios and the use of frontier concepts are mainly employed by the academic community. Accordingly, the cost minimization measures are best defined in terms of cost excess (C_{excess}), to be used in a managerial context including methodological knowledge on frontier analysis.

When analyzing *M&As*, a key measure to be verified is scale efficiency. This can be specified for both convex (*DEA*) and non-convex (*FDH*) situations, through either cost efficiency (C_{eff}) or cost excess (C_{excess}). The scale efficiency is given by the ratio/difference between the two frontiers assuming *CRS* and *VRS*, respectively (see Ray 2004). Hence, in the cost excess (C_{excess}) framework, the scale measure is:

$$S_{Cexcess} = (C_O - C^{*,\,CRS}) - (C_O - C^{*,\,VRS}) = C^{CRS}_{excess} - C^{VRS}_{excess} \geq 0 \tag{8}$$

A *DMU* is scale efficient (or has no cost excess due to scale inefficiency) when it attains the score of 0 for equation (8), meaning that it is simultaneously positioned on both the *CRS* and *VRS* efficiency frontiers. This can occur in *DEA*, in *FDH*, or in both specifications. In contrast, results higher than 0 indicate the excess in monetary terms that should be reduced to reach the cost efficient scale. Note that the outcome of equation (8) is given by the two frontier costs associated with the *CRS* and *VRS* assumptions. The observed cost (C_O) is identical in both specifications.

3.3. A Proposal for Evaluating the Efficiency Gains from M&As

A model for evaluating efficiency gains from *M&As* is proposed taking into account both ex ante and ex post merger perspectives. Furthermore, it considers the managerial and frontier approaches under convex (*DEA*) and non-convex (*FDH*) technologies. A first stage is to test which technology is more appropriate for linking the ex ante and ex post periods' accounting data (C_O) with their corresponding frontier computations (C^*). One can thus determine which frontier method provides efficiency estimations closer to the observed costs, and consequently closer to the true technology.

This task is undertaken through a correlation matrix between the two viewpoints: managerial cost structure and efficiency frontier. What a manager can monitor is the difference in observed costs (*i.e.* accounting data) pre- and post-merger event. Conversely, the frontier approach provides the difference in frontier costs (*i.e.* computed efficient cost) between the ex ante and ex post periods. Specifically, in the case of two merging *DMUs* A and B, the two elements of the correlation matrix are:

$$\begin{aligned} &1\text{: } (C_{O(\mathrm{A})} + C_{O(\mathrm{B})})^{(\text{pre-M\&A})} - C_{O(\mathrm{A+B})}^{(\text{post-M\&A})} \\ &2\text{: } (C^*_{(\mathrm{A})} + C^*_{(\mathrm{B})})^{(\text{pre-M\&A})} - C^{*(\text{post-M\&A})}_{(\mathrm{A+B})} \end{aligned} \tag{9}$$

Note that the pre-*M&A* components indicate the total amount of costs that can be reduced, whereas the post-*M&A* costs illustrate the actual reduction (or increase). In both situations, managers or frontier specialists expect these differences to have a positive result, showing that costs have been reduced ex post. This condition assumes that there are no changes in the levels of outputs produced by each merging *DMU*, otherwise this could partly account for the differences in costs. While the observed costs (C_O) are identical for the two technologies, the frontier costs (C^*) differ between *DEA* and *FDH*. Therefore, two correlation matrices can be formed between part 1 and the two versions of part 2 in equation (9). The matrix with higher correlation points to which technology approximates better the cost movements of *M&As*.

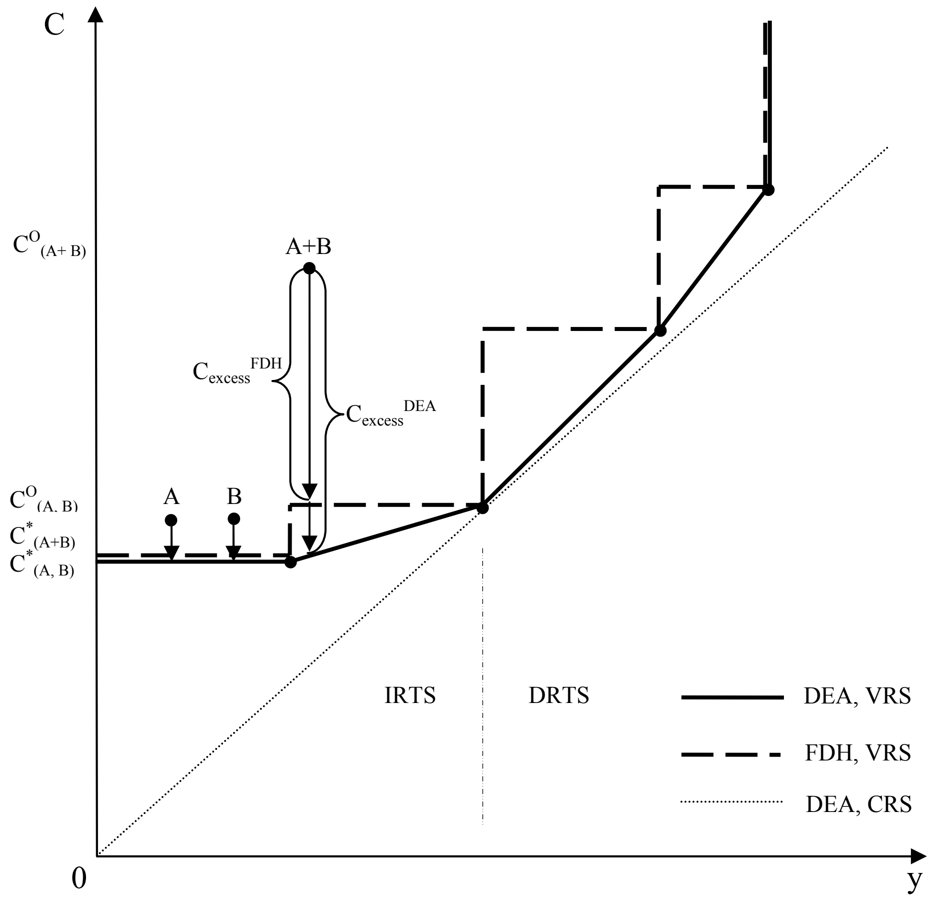
For a second stage of the analysis, an ex ante condition for *M&As* is designed. If one aims for scale economies, then the cost excess attained through merging (*i.e.* the cost that should be eliminated ex post) should be significant. As a result, for two merging *DMUs* A and B, the following inequality should be verified:

$$C_{excess(\text{A})}^{(\text{pre-M\&A})} + C_{excess(\text{B})}^{(\text{pre-M\&A})} < C_{excess(\text{A+B})}^{(\text{pre-M\&A})} \tag{10}$$

This condition must be tested for the ex ante periods (under both convex and non-convex technologies). The left hand side sums up the cost excesses corresponding to the unmerged units, whereas the right hand side computes the cost excess of the hypothetically merged unit. This hypothetical unit is obtained by the backward sum of the inputs and outputs of the merging *DMUs*. Backward mergers have been previously utilized in the literature on efficiency to achieve ex ante knowledge (see, *e.g.*, Tortosa-Ausina 2002).

The rationale behind the condition in equation (10) can be explained through Figure 3.3. Let us suppose that the analyzed period is the year prior to the merger event. The two *DMUs* considering the merger (A and B) are positioned relatively close to the efficiency frontier, in the increasing returns to scale (*IRTS*) part of the graph. If one projects the hypothetically merged *DMU* A+B, the degree of inefficiency, and consequently the cost excess escalate. The positive difference between the cost excess of the merged *DMU* A+B and the separate cost excesses of A and B points to potential gains from merging. The separate *DMUs* A and B show that there is little room for improvement if remaining unmerged. By fulfilling the condition in equation (10), *DMU* A+B indicates that there is room for attaining scale efficiency gains by reducing the high amount of created cost excess.

Figure 3.3. Gains from *M&As*: A Cost Excess Perspective



In contrast, if the inequality in equation (10) is not confirmed, the merger may be directed towards other purposes, such as the diversification of activities or scope economies. In Figure 3.3, imagine that *DMU* A+B, instead of having *IRTS*, is showing decreasing returns to scale (*DRTS*). At the same time, the unmerged *DMUs* A and B remain in the *IRTS* panel. In this scenario, it is probable that the cost excess (C_{excess}) of *DMU* A+B will be smaller than the added cost excesses of *DMUs* A and B. Under these circumstances, one could speculate that the merger is either aimed to different gains than scale efficiency, or it is a political one (*e.g.* due to industry regulations).

Ex post, these potential cost excess gains are evaluated through significant differences between the studied periods. In addition, scale economies gains in terms of monetary excess are also assessed. In this case, the pre- and post-merger periods are compared, thus no backward mergers are required. Using the specification in equation (8), the condition for post-merger scale gains is expressed in monetary terms as:

$$S_{excess\,(\text{A})}^{(\text{pre-M\&A})} + S_{excess\,(\text{B})}^{(\text{pre-M\&A})} \geq S_{excess\,(\text{A+B})}^{(\text{post-M\&A})} \tag{11}$$

Inequality (11) assumes that there are no changes in the activity level of the analyzed *DMUs*. It compares the ex ante (left hand side) and ex post (right hand side) cost excesses due to scale inefficiency. This excess is shown in monetary terms as being higher than or equal to 0. Hence, lower post-merger values designate scale gains from the merger. Inequality (11) is tested in both *DEA* and *FDH* so as to provide clear evidence on the existence of post-merger scale gains and their amount.

4. Sample Description, Variables and Analysis

4.1. Deregulation, Growth and M&As in the Spanish Banking Industry

The Spanish banking industry is constituted by three types of institutions: private banks, savings banks and credit cooperatives. The main difference between the three is the ownership structure. The private banks are private and generally pursue the goal of profit maximization. Some of these private banks are subsidiaries of foreign banks or of other Spanish banks. Conversely, the savings banks are public companies, whereas the credit cooperatives frequently belong to their customers. Additionally, the private and savings banks control over 95% of the banking assets (see Grifell-Tatjé and Lovell 1997a; Kumbakhar *et al.* 2001; Crespí *et al.* 2004). Also, as a consequence of size and organization type, the employed technology is homogenous between the private and savings banks only. Therefore, this study focuses on these two main types of banking units.

This sector is attractive to research due to the growth period that occurred after the disappearance of the regulatory constraints. The first deregulatory efforts were undertaken in the 1960s, but the actual market liberalization took place at the end of the 1980s, beginning of the 1990s. The regulatory reforms were aimed at improving bank competitiveness and converging with the European bank standards. This required banks to implement new strategies. Accordingly, the main deregulation targets were to: eliminate interest rate controls and investment requirements, relax reserve requirements, remove inter-country barriers to competition, enhance branch expansion and consequently facilitate the entry of foreign and local banks at all levels of the Spanish market.

All these deregulatory measures were applied gradually, ending in 1992. Interest rates and commissions were reformed in 1987 and credit limits were removed before 1990. Equal investments for private and savings banks were suppressed in 1989-1992. In 1992 the relaxation of reserve requirements was introduced. Branch restrictions were lifted in 1985 for private banks and in 1989 for savings banks. The new created market changed the status of the Spanish banking industry from that of a closed market to one in which all units could compete via the same financial services and their associated prices and quality characteristics. One can refer to Kumbakhar *et al.* (2001) and Hasan and Lozano-Vivas (2002) for more extensive views on this deregulation process and its consequences.

Adjustments to the new market structure came in different ways for the private and savings banks. On the one hand, private banks aimed at meeting the needs of the new competitive market and the policies of the European Union. These included, among other options, redefining deposits, loans rates and capital standards. On the other hand, savings banks have been the real beneficiaries of the liberalization process. Mostly due to the removal of interest rates and geographical and procedural restrictions, the savings banks grew rapidly and introduced expansion strategies. Specifically, savings banks oriented themselves to opening new branches, increasing their proximity to customers via the *ATM* networks and conducting *M&As*.

This first wave of aggressive *M&As* and growth occurred between 1989 and 1995 (with most *M&As* in 1990). Savings banks, now operating nationwide, reduced their number by approximately 35 percent. At the same time, they increased their number of branches by roughly 17 percent, *ATMs* augmented from 40 per bank in 1986 to 301 in 1995, and their market share reached 45 percent (Kumbakhar *et al.* 2001). Savings banks also changed their strategic orientations, positively increasing their loans to deposits ratios by 37 percent (Kumbakhar *et al.* 2001). This could indicate a change from the production (*i.e.* attraction of both loans and deposits as outputs) to the intermediation approach (*i.e.* banks act as intermediaries between deposits, viewed as inputs, and loans as outputs). Linked to our analyzed topic, one can speculate that one of the causes of the increased market concentration is given by *M&As*.

While the main actors of *M&As* were the savings banks, private banks have also been involved in these events. *M&As* between private banks were generally declared as value maximizing and mostly involved one larger bank which acquired a smaller one. Furthermore, *M&As* of private or savings banks continued even after the beginning of the 2000s (although not as aggressively as in the late 1980s – early 1990s).

There are thus two factors to take into account when forming the sample for the analysis. First, the merger event must be preceded and followed by 2-3 subsequent periods to observe pre-merger behavior and post-merger gains (see Berger *et al.* 1999;

DeYoung *et al.* 2009). Second, the first important wave of *M&As* must be captured together with the following growth period. For these reasons, the analyzed sample consists of yearly data on private and savings banks between 1988 and 2006. The period is also limited due to availability of data. Moreover, foreign banks that showed inconsistent assets-related information have been removed from the dataset. To be more exact, the database provides information on a total of 32 *M&As* (19 of which between savings banks and 13 among private banks).

4.2. Variables and Analysis

The previous section indicated that savings banks may have shifted from a production approach towards an intermediation one. As found in Berger and Humphrey (1997: 197) these are the two main approaches through which the financial institutions are evaluated (see also the survey of Goddard *et al.* (2001)). Their dissimilarities represent the differences in financial behaviors of banking firms. First, banks are considered producers of both deposit accounts and loan services. Hence, they perform under a production approach, a specification which considers as inputs only labor and capital and their costs. Second, banks can be looked at as mediators between deposits and purchased funds that are transformed into loans and financial investments. This is the intermediation approach, in the case of which inputs are represented by funds and their interest cost (*i.e.* the raw material to be transformed) (Berger and Humphrey 1997).

This analysis utilizes the intermediation approach under a cost efficiency definition. Current banking and efficiency studies support this choice, as it is considered to better encompass bank activity (see Berger and Humphrey (1997) and Appendix 3.1). Apart from deposits, labor and assets as inputs, and loans as outputs, other banking dimensions should be included. These may be gains from investments or fee-based operations (see, *e.g.*, Tortosa-Ausina 2004). In establishing the outputs, inputs and input prices there is one more specification difficulty. Spanish accounting formats changed two times during 1988-2006: in 1992 and in 2004. The changes affected both the balance sheets and income statements. Thus, the variables are established for the period 1992-2004, and then their proxies are identified for the rest of the period.

Outputs are (1) loans and other earning assets, (2) investment portfolio and non-interest income (non-traditional output). Inputs are (1) deposits from clients and credit institutions, (2) labor (number of employees) and (3) number of branches. Associated input prices are (1) price of funds (financial costs: interests), (2) price of labor (wages) and (3) price of physical capital (fixed costs). This definition of variables is comparable to the one of Tortosa-Ausina (2004), a study of the Spanish banking industry during the 1990s. Some differences appear due to the changes in the accounting regulations for Spanish financial firms and the resulting need of maintaining homogeneity for all of the analyzed period. Note that the values are either in absolute terms, either in monetary values. For the latter case, the numbers are deflated with respect to the *GDP*. See Table 3.1 for the definition of variables and descriptive statistics.

Table 3.1. Definition of Variables

Variable	Variable Name	Mean	Std. Dev	Minimum	Maximum
Outputs					
y_1	Loans and other earning assets	5399523	15280933	6545	208517711
y_2	Investment portfolio & Non-interest income (non-traditional output)	132820	426273	12	6408983
Inputs					
x_1	Deposits (from clients and credit institutions)	6663118	19738135	842	274443677
x_2	Labor (number of employees)	1987	3992	2	32447
x_3	Branches (number of)	297	557	1	5179
Input prices					
ω_1	Price of funds (financial costs: interests)	0.052	0.056	0.0001	1.835
ω_2	Price of labor (wages)	40.056	14.777	3.696	204.714
ω_3	Price of physical capital (fixed costs)	277.694	528.575	3.434	11160.795

Next, the sample was checked for outliers via the use of the above inputs and outputs. In frontier analysis, outliers, as extremely efficient units, may shape the efficiency frontier and therefore create bias. A common test for outliers is defined by means of the super-efficiency coefficient introduced by Andersen and Petersen (1993) and Wilson's (1993) seminal paper. The test was carried out by means of *VRS* output oriented *DEA*. Units with high super-efficiency are removed from the sample and coefficients are recomputed. The two sets of results are then contrasted. In addition, as indicated by Prior and Surroca (2006), this procedure has to be rerun until the null hypothesis of equality between consecutive efficiency scores cannot be rejected. Through this technique it is determined that roughly 6-7% of the units in the dataset were potential outliers.

The analysis is performed on the outlier-free sample in line with the methodology proposed in Section 3. The frontiers are computed yearly using the complete sample of banking units (merged or unmerged), thus benefiting from sufficient degrees of freedom. Due to data availability restrictions on the *M&As* in the sample, the efficiency gains are evaluated considering a time span of seven years. The seven cost efficiency snapshots are given for three years pre- and post-*M&A* event, plus the year of the merger. Subsequently, the significant differences between periods are shown through the Wilcoxon non-parametric test. This test statistic is dedicated to analyzing related samples (*i.e.* the same *DMUs* and the same measures in different periods) and it assumes no prior distribution, an important aspect when computing efficiency frontiers.

5. Empirical Results

The first stage of the analysis provides the correlation matrices proposed in equation (9). These are presented in Tables 3.2 (for the *DEA* convex technology) and

3.3 (for the *FDH* non-convex technology). At a first glance, the Pearson correlations together with their associated significance levels show that both methods offer rather accurate predictions. However, one should notice that the correlation is higher in the case of the *FDH* non-convex frontier costs. This stronger link between the estimations of the *FDH* method and the observed costs, confirms the theoretical assumptions described in Subsection 3.1. Specifically, the *FDH* frontier is a more exact inner approximation of the true technology (as previously stated by Färe and Li (1998) and Briec *et al.* (2004)).

Table 3.2. Correlation Matrix – Observed Costs vs. *DEA VRS* Convex Frontier Costs

			Observed Costs											
			(t-3)-t	**(t-3)-(t+1)**	**(t-3)-(t+2)**	**(t-3)-(t+3)**	**(t-2)-t**	**(t-2)-(t+1)**	**(t-2)-(t+2)**	**(t-2)-(t+3)**	**(t-1) -t**	**(t-1)-(t+1)**	**(t-1)-(t+2)**	**(t-1)-(t+3)**
DEA Frontier costs	**(t-3)-t**	Pearson Correl.	0.985	0.907	0.505	0.474	0.846	0.700	0.656	0.934	0.720	0.596	0.607	0.855
		Sig.	0.000	0.000	0.023	0.035	0.000	0.001	0.002	0.000	0.000	0.006	0.005	0.000
	(t-3)-(t+1)	Pearson Correl.	0.867	0.984	0.654	0.353	0.808	0.815	0.919	0.833	0.604	0.618	0.738	0.565
		Sig.	0.000	0.000	0.002	0.127	0.000	0.000	0.000	0.000	0.005	0.004	0.000	0.009
	(t-3)-(t+2)	Pearson Correl.	0.569	0.680	0.972	0.703	0.136	0.151	0.601	0.606	-0.123	-0.121	0.183	0.076
		Sig.	0.009	0.001	0.000	0.001	0.567	0.526	0.005	0.005	0.605	0.611	0.440	0.750
	(t-3)-(t+3)	Pearson Correl.	0.598	0.486	0.825	0.995	-0.060	-0.216	0.080	0.691	-0.252	-0.410	-0.284	0.279
		Sig.	0.005	0.030	0.000	0.000	0.801	0.360	0.737	0.001	0.284	0.072	0.225	0.234
	(t-2)-t	Pearson Correl.	0.635	0.665	-0.023	-0.214	0.985	0.963	0.721	0.543	0.975	0.978	0.918	0.735
		Sig.	0.003	0.001	0.924	0.364	0.000	0.000	0.000	0.013	0.000	0.000	0.000	0.000
	(t-2)-(t+1)	Pearson Correl.	0.500	0.660	0.047	-0.316	0.905	0.991	0.849	0.423	0.851	0.950	0.962	0.494
		Sig.	0.025	0.002	0.843	0.175	0.000	0.000	0.000	0.063	0.000	0.000	0.000	0.027
	(t-2)-(t+2)	Pearson Correl.	0.493	0.726	0.455	-0.061	0.685	0.816	0.977	0.452	0.532	0.663	0.878	0.260
		Sig.	0.027	0.000	0.044	0.799	0.001	0.000	0.000	0.045	0.016	0.001	0.000	0.268
	(t-2)-(t+3)	Pearson Correl.	0.922	0.912	0.619	0.543	0.748	0.653	0.711	0.963	0.583	0.504	0.579	0.780
		Sig.	0.000	0.000	0.004	0.013	0.000	0.002	0.000	0.000	0.007	0.023	0.008	0.000
	(t-1)-t	Pearson Correl.	0.483	0.451	-0.263	-0.372	0.918	0.868	0.534	0.374	0.990	0.970	0.859	0.730
		Sig.	0.031	0.046	0.263	0.106	0.000	0.000	0.015	0.104	0.000	0.000	0.000	0.000
	(t-1)-(t+1)	Pearson Correl.	0.388	0.472	-0.211	-0.480	0.894	0.937	0.678	0.287	0.929	0.994	0.942	0.551
		Sig.	0.091	0.036	0.371	0.032	0.000	0.000	0.001	0.220	0.000	0.000	0.000	0.012
	(t-1)-(t+2)	Pearson Correl.	0.386	0.519	0.048	-0.364	0.792	0.869	0.818	0.296	0.774	0.864	0.977	0.421
		Sig.	0.093	0.019	0.841	0.114	0.000	0.000	0.000	0.204	0.000	0.000	0.000	0.065
	(t-1)-(t+3)	Pearson Correl.	0.696	0.552	-0.015	0.045	0.860	0.701	0.453	0.660	0.900	0.776	0.703	0.947
		Sig.	0.001	0.012	0.952	0.852	0.000	0.001	0.045	0.002	0.000	0.000	0.001	0.000

Where, *t* is the period of the merger event.

Table 3.3. Correlation Matrix – Observed Costs vs. *FDH VRS* Non-Convex Frontier Costs

			Observed Costs											
			(t-3)-t	(t-3)-(t+1)	(t-3)-(t+2)	(t-3)-(t+3)	(t-2)-t	(t-2)-(t+1)	(t-2)-(t+2)	(t-2)-(t+3)	(t-1) -t	(t-1)-(t+1)	(t-1)-(t+2)	(t-1)-(t+3)
FDH Frontier costs	(t-3)-t	Pearson Correl.	0.999	0.924	0.617	0.606	0.756	0.606	0.623	0.968	0.598	0.467	0.497	0.801
		Sig.	0.000	0.000	0.004	0.005	0.000	0.005	0.003	0.000	0.005	0.038	0.026	0.000
	(t-3)-(t+1)	Pearson Correl.	0.925	0.999	0.710	0.495	0.765	0.731	0.839	0.906	0.550	0.525	0.625	0.610
		Sig.	0.000	0.000	0.000	0.026	0.000	0.000	0.000	0.000	0.012	0.018	0.003	0.004
	(t-3)-(t+2)	Pearson Correl.	0.624	0.715	0.998	0.810	0.119	0.112	0.532	0.675	-0.157	-0.176	0.075	0.107
		Sig.	0.003	0.000	0.000	0.000	0.617	0.638	0.016	0.001	0.509	0.457	0.753	0.653
	(t-3)-(t+3)	Pearson Correl.	0.610	0.493	0.805	0.999	-0.049	-0.210	0.059	0.700	-0.241	-0.403	-0.305	0.292
		Sig.	0.004	0.027	0.000	0.000	0.836	0.374	0.805	0.001	0.307	0.078	0.192	0.212
	(t-2)-t	Pearson Correl.	0.753	0.761	0.111	-0.056	1.000	0.949	0.746	0.667	0.957	0.932	0.887	0.794
		Sig.	0.000	0.000	0.641	0.816	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000
	(t-2)-(t+1)	Pearson Correl.	0.605	0.730	0.106	-0.211	0.949	0.999	0.853	0.528	0.884	0.950	0.951	0.587
		Sig.	0.005	0.000	0.655	0.371	0.000	0.000	0.000	0.017	0.000	0.000	0.000	0.006
	(t-2)-(t+2)	Pearson Correl.	0.625	0.841	0.528	0.061	0.751	0.856	0.996	0.588	0.571	0.677	0.857	0.352
		Sig.	0.003	0.000	0.017	0.800	0.000	0.000	0.000	0.006	0.009	0.001	0.000	0.128
	(t-2)-(t+3)	Pearson Correl.	0.955	0.886	0.653	0.686	0.663	0.519	0.572	0.996	0.494	0.367	0.407	0.789
		Sig.	0.000	0.000	0.002	0.001	0.001	0.019	0.008	0.000	0.027	0.112	0.075	0.000
	(t-1)-t	Pearson Correl.	0.628	0.587	-0.101	-0.210	0.965	0.893	0.608	0.523	0.996	0.954	0.871	0.803
		Sig.	0.003	0.007	0.671	0.374	0.000	0.000	0.004	0.018	0.000	0.000	0.000	0.000
	(t-1)-(t+1)	Pearson Correl.	0.503	0.568	-0.115	-0.366	0.943	0.961	0.718	0.404	0.956	0.997	0.952	0.633
		Sig.	0.024	0.009	0.628	0.113	0.000	0.000	0.000	0.077	0.000	0.000	0.000	0.003
	(t-1)-(t+2)	Pearson Correl.	0.538	0.672	0.178	-0.224	0.869	0.930	0.893	0.454	0.809	0.883	0.991	0.506
		Sig.	0.014	0.001	0.453	0.343	0.000	0.000	0.000	0.045	0.000	0.000	0.000	0.023
	(t-1)-(t+3)	Pearson Correl.	0.854	0.678	0.227	0.353	0.801	0.598	0.432	0.838	0.781	0.609	0.557	0.985
		Sig.	0.000	0.001	0.336	0.127	0.000	0.005	0.057	0.000	0.000	0.004	0.011	0.000

Where, t is the period of the merger event.

Next, the ex ante condition specified in equation (10) is analyzed. Surprisingly, only 13 *M&As* out of the total of 32 constantly complied with this inequality. Moreover, the condition is confirmed mainly in the case of the *FDH* measure. As indicated in Subsection 3.3., a positive ex ante evaluation points to possible ex post scale efficiency gains through the reduction of the generated cost excess. In this situation the *M&As* can be labeled as value maximizing by means of achieving a better scale. Nevertheless, there are other value maximizing reasons that can be associated with negative ex ante evaluations. These include strategic options such as the diversification of activities and the pursuit of scope economies. The drivers of these *M&As* may well be enhancing the geographical reach and the control of activity risks, lowering the dependencies of certain financial markets and increasing the levels of services offered to the current customers.

Alternatively, as mentioned by Berger *et al.* (1999) and DeYoung *et al.* (2009), *M&As* are also fostered by non value maximizing reasons, such as the managers' own objectives and the influence of regulations. The latter usually appear in the form of safety nets or due to financial instabilities. Most of the *M&As* in the sample occurred during the post-deregulation growth phase (*i.e.* the beginning of the 1990s). Therefore, a central goal of these *M&As* may have well been the attempt of consolidation in view of competition enhancements. This is the case of small savings banks, which additionally acted under the influence of policies instituted by the Spanish central bank.

The efficiency frontier analysis provides another explanation for rejecting the ex ante condition. *M&As* between *DMUs* exhibiting increasing returns to scale (*IRTS*) may result in a new *DMU* characterized by decreasing returns to scale (*DRTS*) (see Figure 3.3). This significantly increases the possibility of not respecting inequality (10) (see Subsection 3.3.).

The above speculations can be tested through the proposed methodology. In what follows, the description of the results focuses on the cost excess measures of scale and technical inefficiencies (see equations 8 and 7 in Subsection 3.2.). Due to their nature, these are presented in monetary terms. Ultimately, the cost inefficiency scores, defined in relative terms, are also presented (see equation 6 in Subsection 3.2.).

The *M&As'* ex post analysis begins by testing the hypothesis of post-merger scale gains (see equation 11 in Subsection 3.3.). Figure 3.4 and Table 3.4 illustrate the evolution of the *M&As'* cost excess due to scale inefficiency for both *DEA* and *FDH*. All the values are expressed in thousands of Euros and indicate the amount of cost to be reduced for reaching an optimal scale. Hence, the scale efficient *DMU* has an excess of zero. The pre-*M&A* cost excess generated by scale inefficiency is given by the sum of the excesses of the merging *DMUs*, while the post-*M&A* results are those of the newly formed *DMU*.

Figure 3.4. *M&As'* Scale Excess Evolution (at Sample Mean Level)

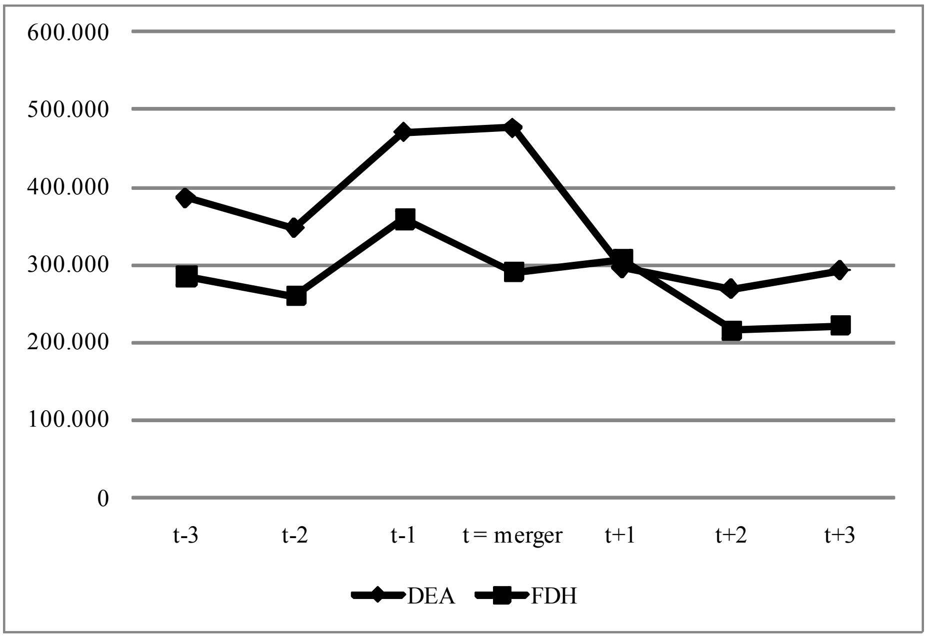


Table 3.4. *M&As'* Cost Excess due to Scale Inefficiency – *DEA & FDH*

DEA Cost Excess due to Scale Inefficiency	Mean	Std. Dev.	Min.	Max.	Quartiles		
					25	50 (Median)	75
t-3	386109.279	616357.146	4429.655	1976218.135	16154.244	44902.135	800736.633
t-2	347274.661	681296.155	1448.387	2772039.631	15161.838	61976.363	269557.635
t-1	471080.538	975749.856	1155.045	4163318.811	17540.895	74242.319	274014.903
t (merger)	476803.455	994781.525	0.205	4300163.279	25120.821	55266.720	426324.875
t+1	295929.460	646120.882	0.000	2973662.447	16146.726	48681.057	176846.047
t+2	267788.324	515462.657	0.000	2017385.150	22372.437	53583.490	215386.840
t+3	292794.348	507591.315	73.735	2041359.317	27883.980	61775.563	214930.403
FDH Cost Excess due to Scale Inefficiency	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Quartiles**		
					25	**50 (Median)**	**75**
t-3	285247.315	360298.763	32952.743	1331650.310	60896.196	135880.936	451435.815
t-2	260240.657	364348.133	30793.875	1763931.516	61319.058	110460.331	300418.142
t-1	358594.394	514788.725	23358.279	2125803.787	77259.781	123586.856	307798.854
t (merger)	290688.210	400475.499	7613.415	1785818.349	52165.293	131645.217	349385.559
t+1	306158.309	473433.250	0.000	1989882.811	66672.701	155195.106	233724.653
t+2	215592.794	298516.572	0.000	1288368.935	49297.782	104562.608	238366.642
t+3	221694.339	358334.154	0.000	1249677.209	46817.589	72317.595	168696.862

One can immediately notice that the merger event produces a rather important increase in the cost excess due to scale inefficiency. This becomes visible during the year previous to the *M&As* and continues in the year of the event. Furthermore, this is valid for both *DEA* and *FDH*. Figure 3.4 shows how, for the case of scale inefficiency, the non-convex cost excess is constantly inferior to the convex one, thus being closer to the analyzed *DMUs*. This supports the methods' assumptions and the hypothesis of proximity between the true technology and the non-convex approximation (see Briec *et al.* (2004)).

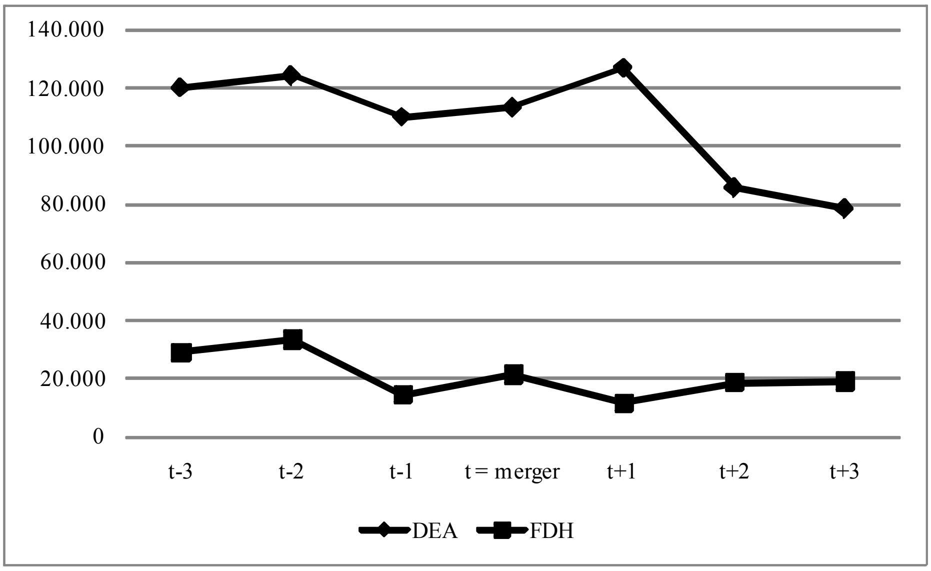
Table 3.5. *M&As'* Cost Excess due to Scale Inefficiency – *DEA* & *FDH* Wilcoxon Tests

DEA Cost Excess due to Scale Inefficiency	**t-3**	**t-2**	**t-1**	**t (merger)**	**t+1**	**t+2**
t-2	0.287	-	-	-	-	-
t-1	0.171	0.313	-	-	-	-
t (merger)	0.484	0.121	0.116	-	-	-
t+1	0.523	0.390	0.073*	0.231	-	-
t+2	0.189	0.695	0.096*	0.022*	0.769	-
t+3	0.526	0.854	0.689	0.157	0.770	0.122
FDH Cost Excess due to Scale Inefficiency	**t-3**	**t-2**	**t-1**	**t (merger)**	**t+1**	**t+2**
t-2	0.543	-	-	-	-	-
t-1	0.048*	0.061*	-	-	-	-
t (merger)	0.465	0.640	0.350	-	-	-
t+1	0.301	0.224	0.627	0.340	-	-
t+2	0.733	0.583	0.016*	0.092*	0.033*	-
t+3	0.852	0.787	0.007*	0.456	0.032*	0.665

*: significant difference.

More significant for the empirical outcome is that for both *DEA* and *FDH* there are observable scale gains post-merger event. The differences in scale driven cost excess between the pre- and post-*M&As* periods are found statistically significant especially in the non-convex case (see Table 3.5). The *DEA* provides significant improvements in the period immediately after the *M&As*, but then the cost excess levels related to scale inefficiency remain somewhat constant. In contrast, the *FDH* technology points out that there is a need for adaptation during the first period. Next, the scale gains are highly significant between the subsequent two periods (*i.e.* *t*+2 and *t*+3). These findings are consistent with the literature reviews on *M&As* stating the need of more analyzed periods for significant gains to be revealed (see, *e.g.*, DeYoung *et al.* 2009). The results also support the hypothesis that scale gains could have been exhausted at *DMU* level prior to the *M&As*. Consequently, the *M&As* offered a solution to attain new scale benefits. These were first created by merging, taking the form of excesses of cost. Second, the scale gains appeared after the implementation of the new management system of the merged *DMU*.

Figure 3.5. ***M&As'*** **Cost Excess Evolution (at Sample Mean Level)**



Another ex post evaluation looks at the cost excess (due to inefficiency) of the *M&As*. While the cost excess due to scale inefficiency considered the *CRS* and *VRS* frontiers, the cost excess caused by technical inefficiency is computed assuming *VRS*. The efficiency literature generally agrees that *VRS* is a better representation of the real technology, particularly for heterogeneous samples. Similarly to the scale measure, the values are expressed in thousands of Euros. They now indicate the excess of cost to be reduced to reach the *VRS* cost efficiency frontier. So, a cost excess of zero identifies the cost efficient *DMUs* (under *VRS*, for *DEA* and/or *FDH*). This analysis can be directly linked to the ex ante condition in equation (10) (see Subsection 3.3.). Therefore, the pre-*M&As* cost excess is computed using the backward merger of the evaluated *DMUs*. Hence, one analyzes if the excess generated by merging is reduced and transformed into post-*M&As* gains (see Figure 3.3 and its explanation in Subsection 3.3.).

Table 3.6. ***M&As'* Cost Excess due to Technical Inefficiency – *DEA & FDH***

DEA Cost Excess due to Technical Inefficiency	Mean	Std. Dev.	Min.	Max.	Quartiles		
					25	50 (Median)	75
t-3	119986.362	152382.320	0.000	607915.104	29524.957	66932.429	151140.381
t-2	124088.809	111053.458	0.000	402134.261	42875.246	90399.378	189435.973
t-1	110103.338	81030.374	0.000	402524.520	50452.850	98843.601	155462.225
t (merger)	113262.396	132582.478	0.000	692409.209	35678.283	82494.011	150373.681
t+1	126898.469	128722.700	0.000	593657.892	52803.247	87894.119	149804.544
t+2	85855.171	75003.331	0.000	358728.146	37894.731	71129.894	116943.654
t+3	78660.198	78639.098	0.000	328118.435	20432.604	43771.307	109762.190
FDH Cost Excess due to Technical Inefficiency	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Quartiles**		
					25	**50 (Median)**	**75**
t-3	28944.426	43109.265	0.000	142047.975	0.000	9406.342	40297.186
t-2	33434.006	55727.743	0.000	173607.275	0.000	0.000	47969.969
t-1	14303.072	25722.940	0.000	114149.251	0.000	0.000	22902.475
t (merger)	21429.594	38931.610	0.000	154588.488	0.000	4485.901	22543.216
t+1	11530.196	22964.028	0.000	110048.730	0.000	0.000	25003.087
t+2	18642.802	31098.857	0.000	115564.516	0.000	0.000	26854.892
t+3	19079.589	32780.300	0.000	108438.834	0.000	0.000	28441.043

The interpretation of the cost excess levels in Figure 3.5 is a bit different than in case of the scale measure. The pre-*M&As* cost inefficiency-generated excess is already given by the prospective (backward) *M&As*. As a result, the excess boost associated with the event year is not observable (as it is for the scale inefficiency). What one should expect is a post-*M&As* reduction of the cost excess due to the inefficiency existing in periods *t*-3 to *t*. As seen in Figure 3.5 and Table 3.6, this is exactly what happens. In contrast to the scale related findings, the significant differences are more present in the convex case. However, the non-convex technology shows lower excesses, and thus better performance than when assuming convexity.

Table 3.7. ***M&As'*** **Cost Excess due to Technical Inefficiency –** ***DEA & FDH*** **Wilcoxon Tests**

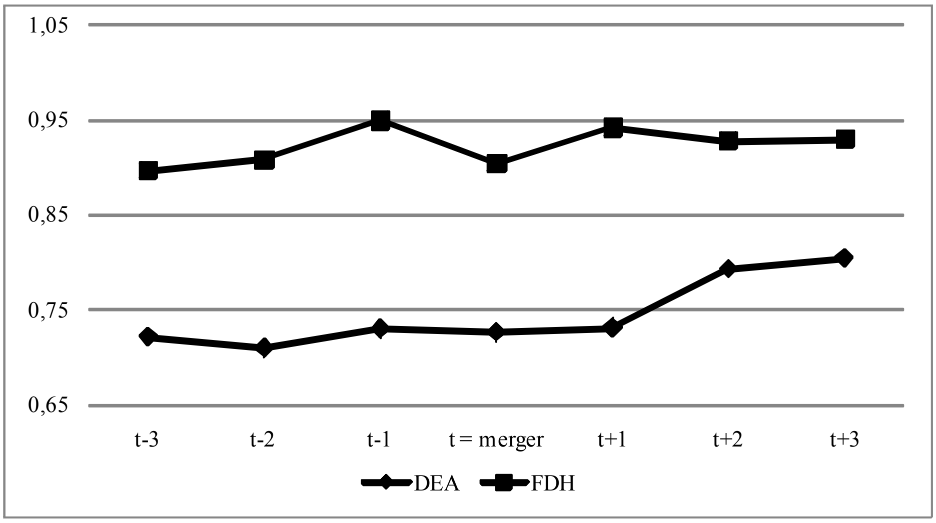
DEA Cost Excess due to Technical Inefficiency	t-3	t-2	t-1	t (merger)	t+1	t+2
t-2	0.664	-	-	-	-	-
t-1	0.178	0.797	-	-	-	-
t (merger)	0.305	0.265	0.192	-	-	-
t+1	0.689	0.910	0.784	0.417	-	-
t+2	0.502	0.165	0.008*	0.733	0.039*	-
t+3	0.679	0.062*	0.016*	0.091*	0.012*	0.174
FDH Cost Excess due to Technical Inefficiency	**t-3**	**t-2**	**t-1**	**t (merger)**	**t+1**	**t+2**
t-2	0.701	-	-	-	-	-
t-1	0.046*	0.088*	-	-	-	-
t (merger)	0.272	0.334	0.157	-	-	-
t+1	0.056*	0.031*	0.691	0.248	-	-
t+2	0.279	0.420	0.381	0.904	0.113	-
t+3	0.279	0.163	0.460	0.554	0.638	0.379

*: significant difference.

The anticipated post-*M&As* reductions of (inefficiency-caused) cost excess are confirmed by the significant differences in Table 3.7. In the convex case, it is clear that the second and third ex post years reveal significant gains from cost excess decreases. Even if not equally significant in the non-convex case, these gains are easily detected via the descriptive statistics results. Also, by means of the theoretical underpinnings of the *DEA* and *FDH*, the fewer significant differences shown by the *FDH* can be explained.

The significant dissimilarities appear by benefiting from the room for improvement in the form of the *M&As'* cost excess due to inefficiency. Nevertheless, the cost excess (or the inefficiency) is always higher when assuming convexity (see Figure 3.2 and its explanation in Subsection 3.1.). This theoretical statement is backed up by the descriptive statistics in Table 3.6. Note in the quartiles' section how approximately half the *DMUs* have no cost excess in the *FDH* panel. At the same time, less than 25% of the sample is cost excess free under the *DEA* framework. Therefore, the room for improvement is always greater in *DEA*, leading to more significant differences.

Figure 3.6. *M&As'* Cost Efficiency Evolution (at Sample Mean Level)



After analyzing the cost excesses due to scale and technical inefficiencies, one can conclude that the revealed post-*M&As* gains can be obtained by the creation of ex ante cost excess. To complement the characterization in monetary terms, Figure 3.6 and Tables 3.8 and 3.9 provide the *M&As'* cost efficiency evolution in relative terms.

Table 3.8. *M&As'* Cost Efficiency – *DEA & FDH*

DEA Cost Efficiency	Mean	Std. Dev.	Min.	Max.	Quartiles		
					25	50 (Median)	75
t-3	0.722	0.176	0.491	1.000	0.571	0.704	0.900
t-2	0.709	0.164	0.469	1.000	0.593	0.640	0.861
t-1	0.729	0.167	0.412	1.000	0.588	0.712	0.886
t (merger)	0.726	0.171	0.363	1.000	0.583	0.693	0.852
t+1	0.731	0.160	0.309	1.000	0.601	0.725	0.842
t+2	0.793	0.155	0.457	1.000	0.655	0.838	0.928
t+3	0.804	0.154	0.569	1.000	0.654	0.794	0.960
FDH Cost Efficiency	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Quartiles**		
					25	**50 (Median)**	**75**
t-3	0.897	0.119	0.611	1.000	0.811	0.912	1.000
t-2	0.908	0.121	0.671	1.000	0.774	1.000	1.000
t-1	0.949	0.080	0.759	1.000	0.907	1.000	1.000
t (merger)	0.904	0.128	0.513	1.000	0.817	0.979	1.000
t+1	0.942	0.121	0.407	1.000	0.909	1.000	1.000
t+2	0.928	0.107	0.567	1.000	0.850	1.000	1.000
t+3	0.930	0.111	0.633	1.000	0.866	1.000	1.000

Due to their theoretical definition, these results are quite similar to the ones of the cost excess due to technical inefficiency. Both convex and non-convex technologies assume *VRS* and the efficient *DMUs* have a score of 1. Lower values designate the degree of inefficiency, indicating the needed percentage of cost reduction to reach the efficiency frontier. Additionally, the analysis is following the backward merger procedure as in the cost excess case.

Table 3.9. *M&As'* Cost Efficiency – *DEA* & *FDH* Wilcoxon Tests

DEA Cost Efficiency	t-3	t-2	t-1	t (merger)	t+1	t+2
t-2	0.099*	-	-	-	-	-
t-1	0.338	0.171	-	-	-	-
t (merger)	0.715	0.405	0.829	-	-	-
t+1	0.434	0.178	0.666	0.572	-	-
t+2	0.086*	0.007*	0.003*	0.003*	0.002*	-
t+3	0.102	0.005*	0.002*	0.002*	0.003*	0.137
FDH Cost Efficiency	**t-3**	**t-2**	**t-1**	**t (merger)**	**t+1**	**t+2**
t-2	0.552	-	-	-	-	-
t-1	0.019*	0.041*	-	-	-	-
t (merger)	0.363	1.000	0.018*	-	-	-
t+1	0.109	0.145	1.000	0.102	-	-
t+2	0.463	0.372	0.309	0.421	0.227	-
t+3	0.552	0.278	0.650	0.407	0.875	0.379

*: significant difference.

In Figure 3.6 one can notice an evolution of the inefficiency analogous to the one of the cost excess in Figure 3.5. The inefficiency is always lower when the frontier is non-convex, and gains are revealed in the two last periods. Once more, these are more significant for the convex technology, fact caused by the above explained theoretical underpinnings of *DEA* and *FDH*. As before, the proportions of efficient *DMUs* are roughly 50% for the non-convex efficiency measure and 25% for the convex one. This interpretation of the cost efficiency frontier is the one usually found in the literature. Thus, it is useful for supporting the managerial focus of the cost excess measures based on scale and technical inefficiencies. All three measures put forth parallel but similar results, revealing the post-*M&As* gains.

6. Concluding Remarks

This paper analyzed the evolution of 32 *M&As* that occurred between the years 1988 and 2006 within the Spanish banking industry. Most of these *M&As* took place during the sector's post-deregulation period, leading the way to enhanced competition and sustainable growth. On the background of the recent financial crisis, this topic attracts vast amounts of interest, as central banks' policies aim to the consolidation of banking units through *M&As*.

The efficiency of *M&As* in banking sectors was evaluated from various viewpoints, however the results were many times unconvincing (see surveys of Berger *et al.* (1999), Amel *et al.* (2004) and DeYoung *et al.* (2009)). One common point of most previous analyses is the use of convex technologies. Therefore, new proposals should consider employing non-convex technologies and cost functions, known to offer more precise inner approximations of the true technology (Briec *et al.* 2004).

Consequently, this study took a managerial approach to cost efficiency and introduced a framework for assessing the gains from *M&As*. In doing so it made use of both convex (*DEA*) and non-convex (*FDH*) technologies. The theoretical characteristics of the *DEA* and *FDH* were tested through correlation matrices. These linked the managerial perspective (*i.e.* the observed costs) and the efficiency estimations (*i.e.* frontier costs, computed for *DEA* and *FDH*). The outcome showed higher correlation in the case of the non-convex frontier costs, confirming the closeness of the *FDH* to the real technology.

Next, the empirical results focused on revealing the gains from *M&As* with respect to cost excesses due to scale and technical inefficiencies. These were defined in monetary terms, an important aspect for the managerial community. The *M&As* were analyzed during a period of seven years, with the merger event as the central point. The main empirical finding is given by the post-*M&As* gains from the reductions of cost excesses due to both scale and technical inefficiencies. The revealed gains were significant mostly during the last two periods (*i.e.* two years after the merger event).

It is probable that even when technical and scale inefficiencies were controlled at local level, the *M&As* provided a way to obtain new cost reductions. The extra cost excess that usually appears via *M&As* can be looked upon as room for improvement in the long run. By merging, the banks created cost excess (due to technical and scale inefficiencies) which was subsequently reduced. These cost excess gains were also confirmed by traditional cost efficiency scores expressed in relative terms. As suggested by the theoretical assumptions of the *DEA* and *FDH* methods, the non-convex estimations always offer lower cost excesses. This is of practical importance, as when the convex frontier does not properly describe the technology, the ex post gains may not be correctly revealed.

Future research should extend the above proposal to include measures of scope efficiency and economies of diversification. These are indicated by the literature on *M&As* as desirable objectives next to the reduction of cost excesses due to scale and technical inefficiencies. To investigate economies of scope, one could refer to models such as the ones found in Grosskopf and Yaisawarng (1990), Chavas and Aliber (1993), Ferrier *et al.* (1993) or Chavas and Kim (2007). Furthermore, it would be interesting to expand the analyzed time span and include cross-country comparisons. The latter could be done at European level, to assess the post-crisis financial policies. However, such post-crisis analyses require more ex post time periods and a larger sample of *M&As*.

Appendix 3.1. Brief Overview of the Literature on the Efficiency of *M&As*

Author (Year of Publication)	Research Objective	Sample	Methodology	Main Results
Akhavein *et al.* (1997)	Examine efficiency and price effects of mergers by means of a profit function.	US bank mergers during the period 1981-1989.	Parametric frontier profit functions applied to data on bank "megamergers". Intermediation approach.	Merged banks show a 16% significant profit efficiency increase with respect to other large banks. More important improvements are found for banks with low pre-merger efficiency scores. It is suggested that these had a greater capacity for improvement.
Altumbas *et al.* (2001)	Estimate scale economies, X-inefficiencies and technical change. To enhance the literature on the cost characteristics of banking industries.	European banks between 1989 and 1997.	Stochastic cost frontier methodologies and the flexible Fourier functional form. Intermediation approach.	Scale economies are common between small and medium banks, and are typically of 5-7%. Efficiency gains from scale economies' exploitation stop once a certain size is reached. X-inefficiencies are larger and vary more in function of time and bank size. It is thus suggested that cost savings can be achieved irrespective of size.
Avkiran (1999)	Reveal the efficiency gains of Australian banks during the deregulation period. Examine the role of mergers in efficiency gains.	Australian trading banks, between 1986 and 1995.	Convex DEA technical efficiency, assuming CRS and input orientation. Intermediation approach.	Overall bank efficiency improved post-deregulation. Acquiring banks were more efficient than target banks. However, the acquiring bank does not always maintain its pre-merger efficiency. The role of mergers in efficiency gains is not necessarily positive.
Berger (1998)	Estimate cost and profit gains from bank mergers.	US banks between 1990 and 1995.	Parametric cost and profit functions. Intermediation approach.	Bank mergers increase profit efficiency relative to other banks. However, there is little effect on cost efficiency. More efficiency gains when banks are inefficient ex ante. Part of the efficiency gains may be from risk diversification.
Berger *et al.* (1993)	Study the efficiency of US banking by means of a profit function.	US banks during the period 1984-1989.	Parametric profit function. Decomposition in allocative and technical inefficiencies. Intermediation approach.	Larger banks are found as more efficient than smaller banks. A proposed measure of "optimal scope economies" shows how joint production is optimal for most banks, while specialization is optimal for others.
Berger and Mester (1997)	Examines the sources of differences in	US banks between 1990 and 1995.	Parametric cost and profit functions.	Profit efficiency is higher for small banks. Profit efficiency is not positively correlated with cost

	measured efficiency. Reviews existing literature and provides new evidence on US banking.		Intermediation approach.	efficiency. Substantial unexploited scale economies.
Bernad-Mocate *et al.* (2009)	Highlight the importance of evaluating *M&As* in the long run. Show that assessments may differ as a function of the used indicators.	Spanish savings banks during the period 1986-2004.	Parametric Cobb-Douglas production function. Financial profitability measures. Fixed effects regression analysis.	Results differ between the productivity or profitability measures. Only one third of the *M&As* show improvements irrespective of the used computation method. Many units do not improve ex post (not even in the long run).
Carbó-Valverde *et al.* (2003)	Compare the effects of mergers on costs, prices, profits, and market competition with the effects of the deregulation.	Spanish banking sector between 1986 and 1998.	Measures of market competition (*i.e.* rate spread, mark-up and Lerner index). Financial ratios, prices and profits. Regression analysis.	The deregulation offered more societal benefits than the wave of mergers. Nevertheless, the improved economic conditions produced the largest benefits. The mergers between Savings banks had no effect on efficiency. Their costs increased at the same pace as those of the non-merging banks.
Carbó-Valverde and Humphrey (2004)	Predict scale-related cost effects from mergers.	Mergers (*i.e.* 22 individual *M&As*) between Spanish savings banks during 1986-2000.	Translog, Fourier, and cubic spline cost functions used to measure scale-related cost effects.	The sign change is correctly predicted ex-ante only one third of the time. *M&As* involving savings banks reduce unit cost (but only by 0.5%), raise asset returns (by 4%) and improve resource allocation. The probability of success is higher for large *M&As* (scale effect) and for *M&As* involving previously merged banks (learning effect).
Crespí *et al.* (2004)	Investigate the governance of Spanish banks.	Spanish banking sector between 1986 and 200.	Multivariate regression analysis (*i.e.* multinomial logit with corporate governance variables).	Negative relation between performance and governance intervention. The performance of savings banks is generally not affected by interventions. Government intervention in the form of *M&As* can have a positive effect on performance. For better results, further deregulation should permit savings banks from different regions to merge.
Cuesta and Orea (2002)	Study the changes in the technical efficiency of the Spanish savings banks.	Spanish savings banks during the period 1985-1998.	Stochastic output distance function. Temporal variation is allowed by relaxing	Merged units show an initial decrease in technical efficiency followed by increases which indicate that the merged banks are more efficient than the non-merged ones. This is especially important in the long

	To test if merged and non-merged firms different patterns of technical efficiency.		monotonicity of the efficiency terms, and by allowing for different efficiency patterns between merged and non-merged firms.	run, as probably merged firms will become even more efficient than non-merged ones. The largest savings banks that merged in the early 1990s are less efficient than non-merged banks.
De Guevara *et al.* (2005)	Analyze the evolution of market power in the main banking sectors of the European Union.	Banking data from France, Germany, Italy, Spain and United Kingdom during the period 1992-1999.	Banking indicators of competition and market power (e.g. Lerner or Hirschman-Herfindhal Indexes). Financial ratios. Parametric measures. Intermediation approach.	Improvements are shown throughout the analyzed period. The main explanatory variables are: size of banks and their operating efficiency, default risk, and the economic cycle. Consolidation decreased marginal costs faster than output prices, indicating an increase in market power.
De Guevara and Maudos (2007)	Study the explanatory factors of market power in the banking system.	Spanish banking sector between 1986 and 2002.	An extension to the model in De Guevara *et al.* (2005) (see above).	An increase in market power is found from the mid-1990s. Size, efficiency and specialization have the great explanatory power. Conversely, concentration is not significant. Cost efficiency improvements appear during the studied period of consolidation, mainly due to declines in marginal costs.
Grifell-Tatjé and Lovell (1996)	Investigate the productivity changes of the Spanish savings banks during the deregulation period.	Spanish savings banks between 1986 and 1991.	Convex, non-parametric Malquist index. Decomposition into efficiency and technological changes. Production approach.	Branching or mergers cannot provide reasons for the extent of the productivity decline over the studied period. Inefficient banks caught-up with the best practices by declining more slowly. In line with related literature, no gains from *M&As* are found. However, one limitation is that the period subsequent to the merger event is too short.
Grifell-Tatjé and Lovell (1997b)	Study the drivers and patterns of productivity change in the Spanish banking sector.	Spanish banking sector during the period 1986-1993.	Convex, non-parametric Malquist index. Decomposition into efficiency, technological and scale changes. Production approach.	Private banks have lower rates of productivity growth, but show greater potential for future growth. These problems are attributed to the impact of diseconomies of scale. Levels of inefficiency are equal between the savings banks involved in *M&As* and the ones which were not involved in merger activities.

Humphrey and Vale (2004)	Importance of using flexible measures to predict economies of scale and estimating cost effects of mergers.	Norwegian banks during the period 1987-1998.	Parametric measures. The study illustrates the inflexibility of the translog cost function. Results are compared to flexible spline and Fourier cost functions.	In general mergers are linked with improvements as they lower costs. Ex ante changes identified through Fourier and spline cost functions are in accordance with the ex post findings. The gains from mergers are not as high as the ones from switching to electronic payments.
Koetter (2005)	Study the success of mergers with respect to cost efficiency.	Mergers between German banks during the period 1993-2003.	Stochastic frontier cost efficiency analysis. Intermediation approach.	Half of the studied mergers were successful in terms of post-merger cost reductions. These gains took up to seven years to be revealed.
Lozano-Vivas (1998)	Investigate the efficiency of the Spanish banking sector during its deregulation period.	The Spanish banking sector between 1985 and 1991.	Parametric Translog cost function: frontier cost efficiency and technological change.	Deregulation is linked with decreases in cost efficiency for private banks, but not for savings banks. Negative technical changes are revealed for the studied period. Results show no significant cost reduction from *M&As* between private or savings banks.
Prior (2003)	Measure the banks' capacity utilization and its effects on firm results.	The Spanish savings banks between 1986 and 1995.	Convex, non-parametric Data Envelopment Analysis. Adaptation to short- and long-run frontier cost efficiency. Measurement of capacity efficiency and input utilization.	The largest part of cost inefficiency is due to capacity inefficiency. Improvements in capacity efficiency are found in relation with the merger wave at the beginning of the 1990s. Main drivers of the improvements: branch network adjustments and reallocation of invested physical capital (an indication of the possibilities of merger events).

General Conclusions

1. General Conclusions, Limitations and Avenues for Future Research

Although the Spanish banking sector attracted vast amounts of interest in past research, the three studies composing this dissertation achieve new understandings of the phenomena. These research papers have been devised to empirically analyze the post-deregulation phase of the industry, a period known for its high levels of efficiency and productivity improvements. Nevertheless, the proposed methodologies should be regarded as being equally relevant for the upcoming post-crisis stage of the economy.

In the context of the financial crisis, the Spanish central bank has designed policies towards optimizing bank activity and the need of consolidation through mergers and acquisitions (*M&As*). As in the post-deregulation case, the main targets of the policies were the savings banks. The guidelines from the central institution indicate that banking operations and their corresponding risks should be better controlled, probably an objective to be attained through bigger size and equity. This represented a hot topic in the Spanish press at the beginning of 2010, as five potential *M&As* between savings banks would change the configuration of the sector. Consequently, banks will introduce changes in their strategic options and significant changes will probably affect the shaping of the efficiency frontiers and the total factor productivity (*TFP*) components.

Therefore, all methodological developments and their empirical applications have been carried out focusing on managerial interpretations and their potential utility for future research. In what follows, three subsections provide specific conclusions for each application, as well as their interconnecting elements and lines for future research.

1.1. Key Findings from Interpreting Bank Productivity and Performance Groups

This chapter introduced a novel conceptual framework for conducting economically meaningful analyses of banking units through their productivity and efficiency changes. By decomposing a Luenberger productivity indicator, managerial interpretations are linked to the efficiency and productivity components of the Spanish private and savings banks. Explicitly, five disentangled productivity dimensions are used to illustrate banking performance. The Luenberger indicator is initially decomposed into technological change and efficiency change. The former describes the evolution of the innovatory practices in the sector. The latter shows how managerial practices, expressed as catching-up effects, impact on the best practice frontier. Next, the efficiency change is decomposed to show the isolated net result of pure efficiency change, jointly with the changes in scale efficiency and input congestion.

As expected for the analyzed period (*i.e.* 1998-2006), the global results for the sector point to important progress. This is shown by the total Luenberger indicator, and was mostly driven by the technological change. One can thus deduce that the sector benefited from the good employment of resources and the use of new information technologies. The end of the analyzed period however, offers what may be the shortcoming of the expansion strategies: negative changes in pure and scale efficiency changes.

When analyzing private and savings banks separately, we observe that at the beginning of the period the latter innovated more. This could be seen as a natural consequence of their aggressive expansion. Simultaneously, the private banks showed more stable and fruitful managerial practices through larger positive efficiency changes. Differences between bank types were fewer during the last studied years. The private banks intensified the technological advancements and caught-up with the savings banks, while maintaining good efficiency change. It is essential to notice that the decomposed indicators support the hypothesis of global competition between private and savings banks.

Subsequently, a cluster analysis uses the Luenberger indicator and its components to group similar banking units. This represents a novel approach for identifying behaviors leading to performance groups. In this way, the productivity and efficiency results and those of the cluster analysis are consistent with each other, an issue that generated debate in the strategic groups' literature. Due to the industry level competition, clusters comprise different types of banking units. As a result, it is shown with greater accuracy where the innovators or good management practices are located. Consistent with the unit level analysis, the technological change is the main discriminating variable, generally accompanied by the Luenberger indicator and the pure efficiency change.

In line with the strategic groups' literature, banking ratios enhance the economically meaningful interpretations of the clusters. We demonstrate in this manner that significant differences (between the already formed groups) also appear with respect to traditional banking dimensions and not only regarding efficiency frontier components.

Additional insights are achieved concerning the Spanish banking industry and its evolution. The significant expansion process of the savings banks could be seen in the congestion component. Their shift from a static position to the growth phase generated congestion in the labor input. Probably, more employees than needed caused the appearance of operations with no value added or high levels of bureaucracy and/or sterile controls. It is convenient to check for congestion in the labor input due to its immediate and visible effect on banking operations. In contrast, the optimal level of assets is better assessed through capacity utilization measures, an aspect that we leave for future research.

These labor congestion problems were later solved, probably through investing in new technologies for the high number of branches and their reorganization. Moreover, no important scale changes are found during the analyzed period. One could speculate that no efficiency gains remain to be given by internal growth. This suggests the option of branch optimization through *M&As* aimed at increasing efficiency. These potential positive impacts of *M&As* on scale efficiency have been studied in Chapter 3 (see also Subsection 1.3. in General Conclusions).

This empirical application acknowledges its methodological and sample related limitations. On the one hand, the time period could be enlarged. On the other hand, in the case of similar industry configurations, international comparisons could be introduced.

1.2. The Usefulness of Technology-Based Total Factor Productivity Benchmarking

This methodological proposal and its illustration are in accordance with the competitive environment analyzed in the previous chapter. Benchmarking is understood not only as the search and emulation of best practices, but as a comparison against whichever competitor a firm may choose. Through this approach, a gap is closed between benchmarking and multi inputs and outputs *TFP* frontier analysis. This task is undertaken by adapting Bjurek's (1996) Hicks-Moorsteen *TFP* (*HMTFP*) index to benchmarking purposes and creating a new framework for setting strategic objectives and analyzing firm performance.

When comparing against efficient companies, the measures show whether the firm has a best or worst market position and, if existing, the distance separating it from the efficient benchmark. As stated by prior literature, this is also a way to discover, understand and implement new organizational practices. Conversely, comparisons can be simply approached as a part of strategic planning by selecting an inefficient but attractive target. In this scenario, the benchmark can be a local competitor, other members of the firm's strategic group or any other firm for that matter. Both cases offer *TFP* and efficiency frontier information, useful for organizational learning and strategic planning.

A method related implication is that the *HMTFP* index deserves greater attention in the literature. This Hicks-Moorsteeen type index solves the known shortcomings of *TFP* measurement under variable returns to scale. In addition, in its general specification, it is always well-defined and does not lead to infeasible results. This is a vital aspect for benchmarking analysis. One should consider that managers do not perform sample level analyses, but firm level ones where unit specific results must always be provided.

By mathematical manipulations of the *HMTFP* index, a flexible tool for benchmarking investigations has been attained. Three different measures are specified: (1) static benchmark analysis, (2) fixed base and unit benchmark analysis, and (3) dynamic analysis and benchmarking decomposition. Each of the three is shaped by different assumptions and pursued goals. They all include fixed unit benchmarking (scarcely used in prior studies) and/or base technologies (traditional frontier benchmarking).

Through each of these approaches, the manager is able to scrutinize different facets of firm activity. However, even if these benchmarking indices are defined as being stand alone, they can be potentially combined to achieve wider viewpoints for decision making.

This study illustrated the proposed methods within the Spanish industry, and by making use of an arbitrarily selected efficient benchmark. In future empirical research, each firm may consider its own criteria for benchmarking, such as strategic group membership or any kind of market variables. These are interesting lines of research which can be implemented, as in the case of our previous chapter, whenever similar configurations are encountered in the industry.

1.3. Main Outcomes of Revealing Cost Excess Gains from Mergers and Acquisitions

The motivation of this chapter is threefold. First, on the background of the financial crisis, the central institutions of various European countries indicate the need of consolidation through *M&As*. Consequently, it is useful to re-assess existing *M&As* in the view of the upcoming wave of such events. Second, as found in our chapter of bank productivity and performance groups, no efficiency gains remained to be given by internal growth. Thus, an option could be conducting *M&As* aimed at efficiency increases. Third, past efficiency studies analyzed the bank *M&As* but often found inconclusive results. A common aspect of most of these prior studies is the employment of convex technologies. We speculate that the inconclusive results may be partly due to this convexity assumption. Hence, new analyses should consider using non-convex technologies and cost functions, known to offer more precise inner approximations of the true technology (as suggested by Briec *et al.* 2004).

A managerial approach was taken to re-asses the ex post gains from 32 *M&As* that occurred in the post-deregulation growth phase of the Spanish banking industry. This is done by estimating both convex and non-convex efficiency frontiers. Furthermore, by correlating the observed costs with the convex and non-convex efficiency measures, it is confirmed that the non-convex frontier costs are closer to the real technology. The post-*M&As* gains were revealed as potential reductions of cost excess caused by scale and technical inefficiencies. This monetary terms' specification was selected to enhance proximity to managerial communities. Gains were encountered as being significant after two ex post periods, while the decreases in cost excess were due to evolutions in both scale and technical inefficiency.

In situations in which scale and technical inefficiencies were under control at local level, the *M&As* showed a way to achieve new cost reductions. When merging, banking units generated extra cost excess (due to scale and/or technical inefficiencies). This was then reduced, fact also confirmed through traditional cost efficiency measures expressed in relative terms. Finally, it is of practical importance to consider that non-convex estimators always find lower cost excess than the convex ones. When convex frontiers do not accurately describe the technology, ex post gains may not be correctly revealed.

Although various future lines of research are available, there is one main direction to follow. Proposals should be extended to include measures of scope efficiency and economies of diversification. These are known as central objectives for *M&As* (next to cost excess reductions) and can be scrutinized through methods such as the ones in Grosskopf and Yaisawarng (1990), Chavas and Aliber (1993), Ferrier *et al.* (1993) or Chavas and Kim (2007). Future studies could be devised at European level, to evaluate the success of post-crisis financial policies.

1.4. General Limitations and Avenues for Future Research

As with all empirical work there are areas that could be enhanced, thus revealing avenues for future research. Apart from the specific limitations indicated in each chapter and in the three previous subsections, there remain a few issues worth mentioning.

First, there is the question of how to define the inputs and outputs for the efficiency analysis of banking institutions. As stated by Berger and Humphrey (1997: 197), "there are two main approaches to the choice of how to measure the flow of services provided by financial institutions" (see also the survey of or Goddard *et al.* (2001)). These are the production and the intermediation approaches and, depending on each case, they may yield distinct results. The main difference between the two is whether to consider deposits as an output (production approach) or as an input (intermediation approach)[9]. There is no clear conclusion on which is best (although the latter is becoming increasingly popular), and consequently each study selects the fitting definition, given the characteristics of the analyzed industry. For instance, Chapters 1 and 2 use the production approach, while Chapter 3 employs the intermediation approach.

In would be interesting to test in future research the difference in findings when utilizing a wider range of input and output specifications. By means of robustness checks allowed by the various definitions, the proposed methodologies and linked empirical findings could be supported more thoroughly.

A second general limitation of the present study, and accordingly a future research avenue, is the need of measuring risk. This is essential for the post-crisis context and crucial when deciding on whether to conduct *M&As*. One option could be to introduce risk variables into the efficiency measures and *TFP* indicators, thus obtaining risk-adjusted estimations. For example, banking ratios defining the risk environment may be used jointly with variables such as percentage of insolvency provisions or simply the risk of assets. However, to perform such post-crisis analyses more ex post time periods are required.

[9] The methodology sections in all three chapters further explain the distinction between the production and intermediation approaches and the reasons for selecting one or the other.

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