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Bank productivity and performance groups: A decomposition approach based upon the Luenberger productivity indicator ☆

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ABSTRACT

The purpose of this paper is twofold. First, in the framework of the strategic groups' literature, it analyzes 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, 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 productivity components. Finally, following the strategic groups' literature, supplementary insights are gained by linking these performance groups with 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 in a dynamic perspective. 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 productivity indices 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 are based on the more recent Luenberger productivity indicator (Chambers, 2002), which measures 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.[1] 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

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[1] The issue of zero values in the indices and indicators must be distinguished from the issue of zero inputs and outputs in the data matrices constituting the technology. See Färe et al., 1994, pp. 44–45 for the exact conditions on these data matrices. However, zero inputs or outputs do not pose a problem for computing the proportional distance function in general (see Section 2 for its definition).

[2] As Chambers, 2002, p. 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."

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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 use proportional distance functions that are compatible with the goal of profit maximization, while the Malmquist indices 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 provide a supplementary analysis to reach further 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, 1997; 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, 1997; Lozano-Vivas, 1997; Prior, 2003; Tortosa-Ausina, 2003; Crespí et al., 2004; Zúñiga-Vicente et al., 2004; Más-Ruíz 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 productivity indicators in these respects is 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 (1992), 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 functions underlying the Malmquist indices 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, p. 751 "these Luenberger indicators are novel because they are based on a translation (not radial) representation of the technology and, thus, are all specified in difference (not 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 $x = (x_1, \dots, x_N) \in R^N_+$ and $y = (y_1, \dots, y_M) \in R^M_+$ be the vectors of inputs and outputs, respectively, and define the technology by the set $T^t(x^t, y^t)$, which represents the set of all output vectors (y^t) that can be produced using the input vector (x^t) in the time period t:

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

On occasion, we use the input set $L^t(y^t) = \{x^t : (x^t, y^t) \in T^t(x^t, y^t)\}$ to characterize technology.

Following Briec, 1997, p. 105, the proportional distance function is defined as:

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

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:

$$\begin{aligned} L^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{1}{2}[&(D^t(x^t, y^t|CRS, SD) - D^t(x^{t+1}, y^{t+1}|CRS, SD)) \\ &+ (D^{t+1}(x^t, y^t|CRS, SD) \\ &- D^{t+1}(x^{t+1}, y^{t+1}|CRS, SD))]. \end{aligned} \tag{3}$$

The indicator is defined with respect to technologies imposing *CRS* and strong disposability of inputs and outputs (henceforth *SD*). 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 avoids an arbitrary selection among base years (see Chambers et al., 1996).

The above definition can be decomposed into two components:

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

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*). As in the case of Eq. (3), the technology is defined assuming *CRS* and *SD*. *EC* measures the evolution of the relative position of a given observation with respect to a changing production frontier. This catching up or falling behind is often interpreted as reflecting managerial effort. However, this study – like many others – is lacking a direct indicator of management quality. 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. Depending on the positive or negative sign, these *EC* and *TC* components represent efficiency improvement or deterioration and technological progress or regress, respectively.

This decomposition is similar to the basic one known for the Malmquist index (see Färe et al., 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., 2011). Subsequently, we propose a decomposition of the Luenberger indicator similar to the one applied to the Malmquist index by Färe et al., 1994, pp. 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*).

Apart from the above technology assumptions of *CRS* and *SD*, this decomposition also 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:

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

where

$$\begin{aligned} PEC^{t,t+1}(x^t,y^t,x^{t+1},y^{t+1}) &= D^t(x^t,y^t|VRS,WD) \\ &\quad - D^{t+1}(x^{t+1},y^{t+1}|VRS,WD), \end{aligned} \tag{6}$$

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

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

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] The latter three efficiency components can have positive or negative signs to indicate improvements or deteriorations.

Fig. 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 graphically and, as represented in Eq. (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 unit k is situated in period t ((x_k^t, y_k^t) in the figure) to the frontier in $t(D^t(x^t,y^t|CRS,SD)$ in Fig. 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 $t+1$ ($D^{t+1}(x^{t+1},y^{t+1}|CRS,SD)$ in Fig. 1).

As observed in Eq. (7), the *SC* represents the movements in scale efficiencies between two periods. These scale efficiencies 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 Fig. 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.

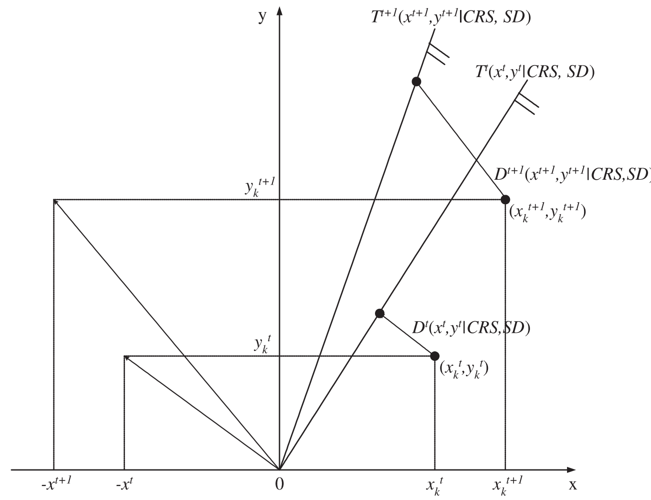

Fig. 1. Efficiency change and technological change.

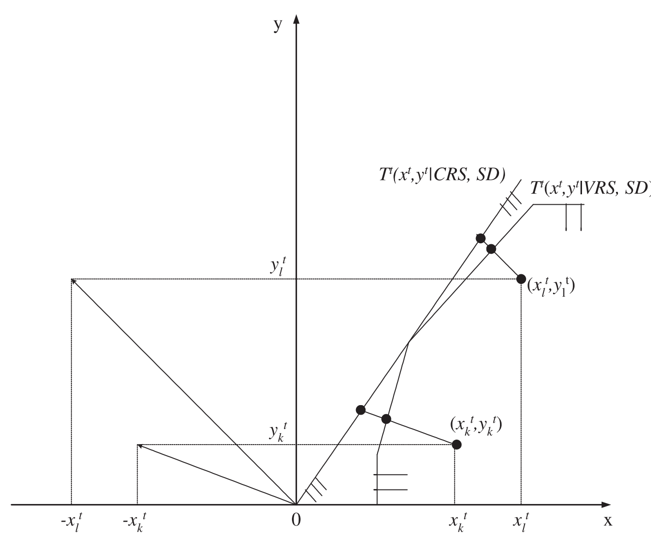

Fig. 2. Scale inefficiency (adapted from Färe et al., 1994, p. 75).

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, p. 75). Fig. 3, assuming a technology with two inputs needed to produce one output, shows that the input mix corresponding to vector x_j^t is congested due to input 1, as the inefficiency in *SD* is greater than in *WD*. Consequently, input vector x_k^t is not congested since the inefficiency in *SD* is equal to the one in *WD*.

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 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

[3] This formulation follows the Malmquist decomposition in Färe et al., 1994 p. 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). All linear programs included a refinement guaranteeing that projected outputs remain non-negative (see Briec and Kerstens, 2009).

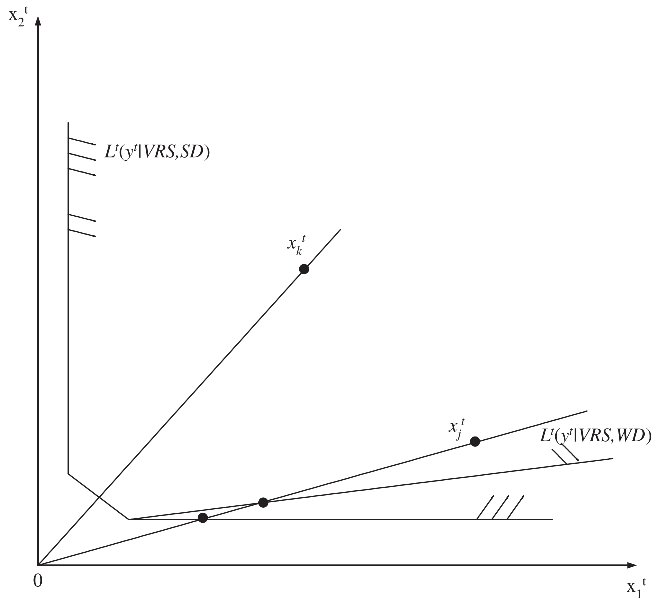

Fig. 3. Input congestion (Färe et al., 1994, p. 76).

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 systematically respond to the competitor's initiatives in a 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, p. 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 existing 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, p. 445 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, according to Ketchen and Shook (1996) this method allows for deductive, inductive or cognitive approaches. In the deductive approach there is a strong link with theory, and thus a priori expectations exist with respect to the employed variables and the nature and number of groups. For the inductive method there are no such prior expectations, and hence one should use as many variables as possible. In this case neither the variables nor the nature or number of groups are derived from deductive theory. Finally, the cognitive approach relies on perceptions and expert information from prominent actors (*e.g.* industry executives). Consequently, this variety of available approaches to cluster analysis is an important feature which permits the use of diverse theoretical frameworks.

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. Classical approaches are those of Kolari and Zardkoohi (1987) and Zúñiga-Vicente et al. (2004) that use traditional, non-frontier based banking ratios as inputs for cluster analysis.

By contrast, this contribution follows a small, rather recent literature that constructs strategic groups (most often using some cluster analysis technique) based upon frontier-based efficiency results. Day et al. (1994, 1995) are the seminal contributions arguing that strategic groups should be based upon static non-parametric efficiency results (also known as data envelopment analysis (*DEA*)) to have a coherent performance interpretation. This contribution has been followed by a series of others: examples include Athanassopoulos (2003), Prior and Surroca (2006), Sohn (2006), and Po et al. (2009), among others. Of course, there is some variation between these articles. For instance, Athanassopoulos (2003) employs peer information to distinguish between groups, while Prior and Surroca (2006) utilize differences between marginal rates of substitution (transformation) between inputs (outputs) obtained through *DEA* models as a foundation for clustering.

From this discussion, we draw the conclusion that clustering based upon static frontier efficiency results guarantees a coherent interpretation of strategic groups reflecting performance differences.[4] However, we think it is important to add a new dimension to this literature by focusing not only on efficiency levels at given points in time, but to capture the evolution of efficiency over time by means of a frontier-based productivity indicator. Indeed, strategic or performance groups also have a time dimension in that similar firms within each group can be supposed to pursue some coherent growth patterns following similar strategic plans. By now adopting a productivity indicator to distinguish the technological and efficiency changes over time, we characterize the dynamic behavior of all firms within the same sample over a given time period. In brief, the detailed Luenberger decomposition yields results that can be employed as inputs into a cluster analysis to distinguish performance groups from a dynamic perspective. To our knowledge, this adds a new, dynamic perspective to this existing literature.

4. Data, variables and methods of analysis

4.1. Description of the sample

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, 1997; Cuesta and Orea, 2002; Zúñiga-Vicente et al., 2004). Consequently, the 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.

[4] Notice that sometimes frontier-based performance results are combined with a more traditional ratio-based cluster analysis: Ray and Das (2010) are a case in point.

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 a small fraction of the banking activity. 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 and serve the same market, the sample is formed of these two bank types starting with the year 1998. Thus, it is assumed that private and savings banks are in competition in terms of productivity and efficiency. 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, p. 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 more clearly the eventual changes in the productivity indicators between both periods.

First, we tested for the possible 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 (1993) super-efficiency measure together with Wilson (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 banks 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 banks.

4.2. Input and output variables and methods 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, p. 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. 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) 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). 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, computed in accordance with the formulation presented in Section 2, and (2) the cluster analysis and the associated significance tests.

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 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 extended through performance ratios practitioners use when referring to the banking industry.

In line with banking related strategic groups research (see Mehra, 1996; Athanassopoulos, 2003; Zúñiga-Vicente et al., 2004; Más-Ruíz 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 (geographic 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).[5]

These banking ratios extend our analysis to enhance the understanding of the identified performance groups, and to illustrate differences between the productivity and efficiency measures and the traditional ratio approach popular among researchers and practitioners. Obviously, the selected ratios have their limitations. For instance, variable 1 assumes a constant and positive propensity of clients to use *ATMs*, but we do not have any information on this. Similarly, variable 2 is sensitive to population density differences. Therefore, all six ratios must be regarded with some caution. This part of the analysis just intends to be supplementary to the Luenberger decomposition and the resulting performance groups.

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, p. 546) state, "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 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 reports the productivity decomposition scores for the two samples. Table 1 and Fig. 4 present the associated descriptive statistics. Notice that the entire analyzed sample is maintained as no infeasibilities appear in the computations. With respect to the studied years, 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 improvement since the higher value is in the second period. This can be observed in Fig. 4 through the roughly 2-to-1 ratio

Table 1
Descriptive statistics.

		Mean	Std. dev.	Min.	Max.
1998–2002					
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					
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

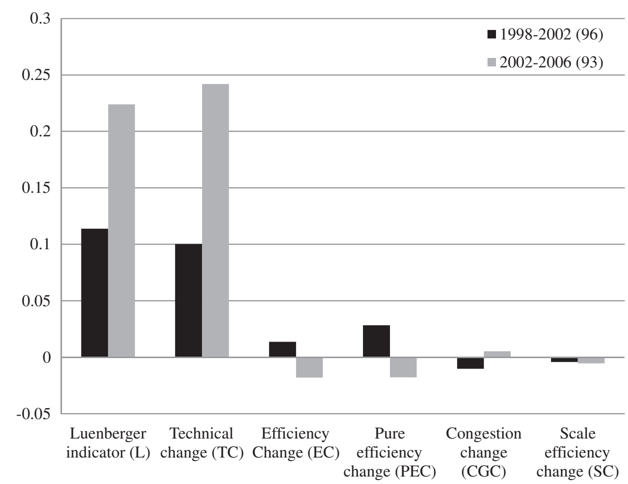

Fig. 4. Luenberger decomposition: sample mean values.

between the two time periods for the mean values of the Luenberger measure (*L*) and the technological change (*TC*). First, this could 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 may form the basis of the positive shifts of the frontier (see the *TC* results of 0.24 in 2002–2006 and 0.10 in 1998–2002).

However, through the decomposed factors we can identify that the two periods are not entirely similar. Even if the Luenberger indicator (*L*) and the technological component (*TC*) are quite higher in the second period, this is not the case for the rest of the components. At a first glance, Fig. 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 may be an indication of successful management (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 alarming as they are in the vicinity of zero). Thus, it is possible that the territorial expansion offered some advantages initially, while problems with the use of inputs and

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

outputs appeared only 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 zero, hence congestion remains apparently non-problematic.

5.2. Relation between private and savings banks according to the luenberger indicators

Table 2 and Figs. 5–8 present results according to the type of bank. These are similar to the ones related to the total sample. Moreover, as some components are showing better results for private banks and others for savings banks, these results may reveal there is fierce competition. Using Table 2 and Fig. 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*).

In the second period, the Luenberger measure (*L*) distributions show no significant difference between both bank types. This is consistent with the competition assumption in terms of productivity. 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 2 and Fig. 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 Section 5.1.

Further insights can be achieved comparing the private and savings banks between the two periods on Figs. 7 and 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 Section 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 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 pure efficiency change (*PEC*) component obtained for the second analyzed period. However, at the same time an improvement of savings banks is found in the congestion change (*CGC*) indicator.

One can imagine 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 2 and Fig. 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

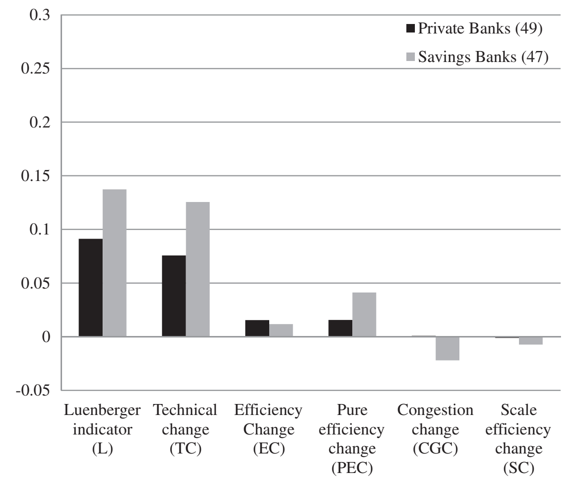

Fig. 5. Luenberger decomposition for 1998–2002: mean values by bank type.

Table 2
Luenberger decomposition: results per bank-type.

		Mean	Std. dev.	Min.	Max.	Li test (*t*-stat./*p*-value)
1998–2002						
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						
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.

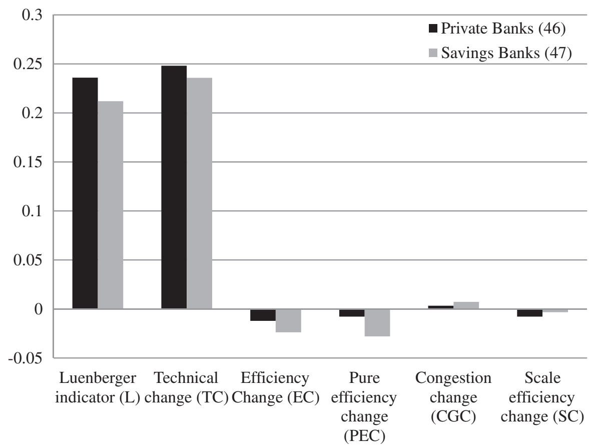

Fig. 6. Luenberger decomposition for 2002–2006: mean values by bank type.

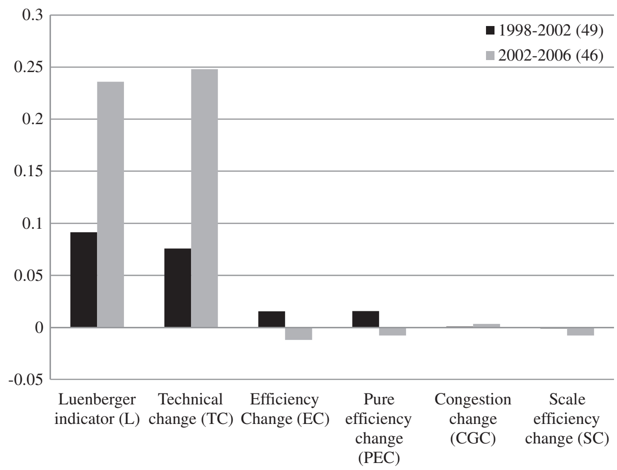

Fig. 7. Luenberger decomposition for private banks: mean values by period.

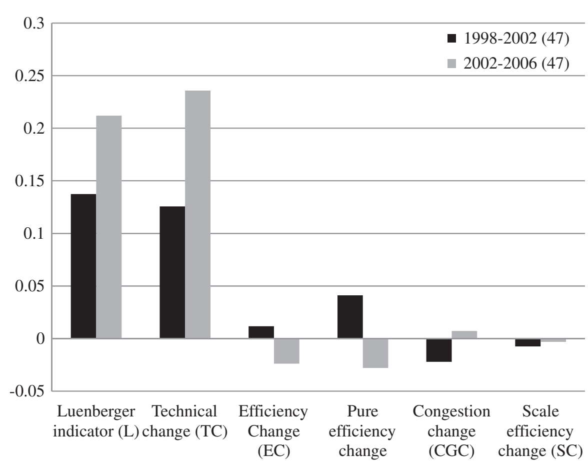

Fig. 8. Luenberger decomposition for savings banks: mean values by period.

realized, the savings banks may have directed their efforts to solving the congestion problem. Therefore, the congestion change component (*CGC*) ends up with 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 3 and Fig. 9 (descriptive statistics) and Table 4 (Li test significance differences). For both 1998–2002 and

Table 3
Luenberger decomposition: group level descriptive statistics.

		Mean	Std. dev	Min.	Max.
1998–2002					
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
	2 (29)	−0.0383	0.0624	−0.2954	0.0102
	G3 (40)	0.0199	0.0560	−0.0957	0.1945
2002–2006					
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.

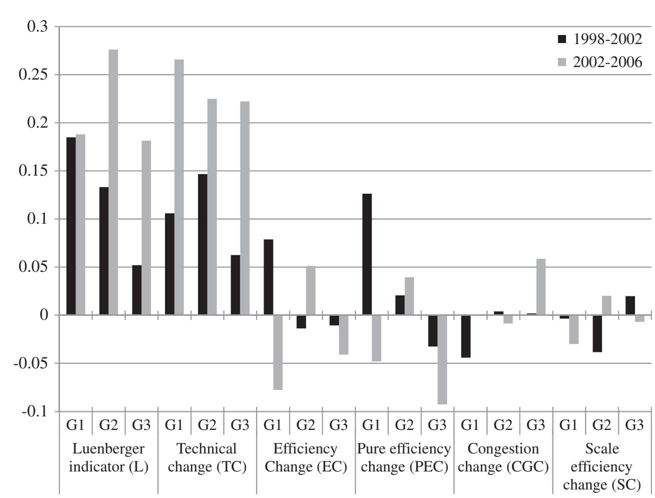

Fig. 9. Luenberger decomposition: mean values at group level.

Table 4
Luenberger decomposition: group level Li test results.

		L	TC	EC	PEC	CGC	SC
1998–2002							
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							
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.

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, there is no stability between the two analyzed time periods. These changes can 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 are treated as independent.

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 Fig. 9), it is noticed that this result can be based on the significantly higher pure efficiency change (*PEC*). It is obvious from Fig. 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.

The second group is mainly defined by the significantly superior technological change (see 1998–2002 *TC* in Table 3 and Fig. 9). Thus, this performance group probably 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 4 and Fig. 9), the Li test indicates there are significant differences among the distributions of these scores. Consequently, one could speculate that banks 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 4 and Fig. 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. Furthermore, the congestion change indicator (*CGC*) is significantly superior to the other two performance groups, an indication of improvements in labor utilization.[6]

5.4. Linking performance groups with banking ratios: supplementary analysis

Following this characterization of performance groups, this supplementary analysis attempts to develop some additional interpretations. By associating the banking ratios defined in Section 4.2. with the performance groups, Tables 5 and 6 present descriptive statistics and test statistics. Interpreting these 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 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*).

Group 2 is significantly ahead concerning the interest margin per employee ratio, one of the performance measures. While it also has superior mean values for the other two performance proxies, it

[6] An appendix containing graphical interpretations of the Li tests is available upon request.

Table 5
Banking ratios: group level descriptive statistics.

		Mean	Std. dev	Min.	Max.
1998–2002					
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					
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.

Table 6
Banking ratios: group level Li test results.

		ATM/TA	Branch/TA	IntMarg/Empl	Risk	ROA	ROE
1998–2002							
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							
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.

is not always significantly better than groups 1 and 3. Its characterization by higher technological change (*TC*) can be theoretically related with a good outcome in the *ATMs* divided by total assets ratio (a proxy for 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*.

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 by good results in terms of Luenberger (*L*) and efficiency change (*EC*) indicators. The latter may be an indication of good management. 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 these phenomena. This is done by means of a decomposition of a Luenberger productivity indicator leading to productivity and efficiency interpretations. Indeed, the main decomposition into technological change (*TC*) and efficiency change (*EC*) intends to shed light on the impact of innovation in shifting best practice frontiers on the one hand, and on the catching-up or falling behind effect revealing somehow managerial success or failure on the other hand.

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.

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 empirical findings, other interesting phenomena are revealed. For instance, taking advantage of the deregulation, the savings banks initiated an important expansion process. This movement from the static market situation to the growth phase seems to have created congestion issues in the labor input. These have probably been solved by investments in new technologies dedicated to the high number of branches that had to be organized. Furthermore, 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 be directed to branch network optimization through potential mergers and acquisitions aimed at increasing 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.

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