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Discussion Papers in Accounting and Finance

Behind DEA Efficiency in Financial Institutions

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Number AF02-7

March 2002 **ISSN 1356-3548**

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This version: February 2002
JEL: G21

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Cecilio Mar Molinero's work was supported by a grant from the Ministerio de Ciencia y Tecnologia (Spain) under the Ramon y Cajal Programme.

BEHIND DEA EFFICIENCY IN FINANCIAL INSTITUTIONS

ABSTRACT

DEA has been extensively used to measure the efficiency of financial institutions. Its advantages are clearly understood. But there are many unresolved problems. There are various views based on different modelling philosophies of what constitutes inputs and outputs in a financial institution. The paper explores up to what point the various combinations of inputs and outputs are equivalent, and up to what point the efficiency score obtained by a given institution changes under the various combinations of inputs and outputs. The extent to which two institutions that achieve the same efficiency score arrive at it following different strategies is explored with the aim of finding out what is behind such a score.

It is suggested that, not one but many different DEA specifications, containing different combinations of inputs and outputs, be modelled and that the results be analysed with the tools of multivariate statistics. Particular emphasis is placed on using tools that visualise the main characteristics of the data. By-products of the approach proposed here are the creation of league tables of financial institutions in terms of efficiencies and the possibility to assess strengths and weaknesses of individual institutions. This methodology is applied to the particular case of Spanish savings banks (Cajas de Ahorros) and proves to be particularly rewarding.

KEY WORDS

Efficiency, savings banks, Principal Component Analysis, banking, Data Envelopment Analysis.

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1. INTRODUCTION

Efficiency is a key concept for financial institutions. It has long been studied. A review of 130 such studies in 21 countries is given by Berger and Humphrey (1997). Berger and Humphrey classify papers according to the technical approach employed, which they identify as parametric- Stochastic Frontier Approach (SFA), Distribution Free Approach (DFA), Thick Frontier Approach (TFA)- or non parametric- Data Envelopment Analysis (DEA), Free Disposal Hull (FDH), Index Numbers (IN), Mixed Optimal Strategy (MOS). By far the most popular technical approach is DEA, which was applied in 62 of the papers surveyed. DEA is appropriate for sets of homogeneous units with similar inputs and similar outputs since it performs multiple comparisons using a Linear Programming based approach. The assumptions are minimal. Inputs and outputs do not need to be measured in the same units, which adds to the advantages of the methodology. A survey of the more restricted area of DEA applications to bank branch performance is given by Schaffnit et al. (1997). Some recent references on the application of DEA to financial institutions are Dekker and Post (2001), Pastor et al. (1997), Hartman et al. (2001), Kuosmanen and Post (2001), Seiford and Zhu (1999), Saha and Ravisankar (2000), and Athanassopoulos (1997).

For the purposes of this paper, it will be useful to make a distinction between model and specification in a DEA context. Different philosophical approaches as to what a financial institution does, and what is meant by efficiency will lead to different models; see Berger and Mester (1997) for a full discussion. Two basic models are prevalent in the literature: intermediation and production. Specification will refer to a more restricted concept: the particular set of inputs and outputs that enter into model definition.

The variety of models and specifications for financial efficiency analysis is reflected in practice. The selection of inputs and outputs varies from study to study, giving an impression of confusion. For example; a particular item, such as deposits, may be treated as an input or as an output according to whether the institution is modelled from the point of view of production or from the point of view of intermediation, see Athanassoupoulos (1997). This is a matter of concern, as the level of efficiency of a financial institution may depend on the particular choice of inputs and outputs. It may be puzzling for the manager of a bank branch to discover that it is possible for different researchers to arrive at different conclusions about the efficiency of a bank branch when using the same technique (DEA). However, this confusion may be more apparent than real, since alternative specifications may be equivalent and the case may never arise. The study of the extent to which two different specifications are equivalent is one of the purposes of this paper.

Model and specification selection are not the only issues addressed in this paper. We wish to go behind the efficiency score. Two financial institutions may achieve the same DEA efficiency under a given model and under a common specification, but they may still be very different. Efficiency, being a mere score, may be compatible with a variety of management strategies. Imagine two institutions that achieve the same efficiency, one may have specialised in the production of a particular output and the other on the good use of a particular input. These differences will, of course, be reflected in different weight structures for inputs and outputs, and could be identified by means of such techniques as cross-efficiency analysis; Doyle and Green (1994). Here we propose a new methodological approach to strategy identification for financial institutions based on multivariate statistical analysis. This approach has the advantage of visualising the way in which a particular DEA score has been achieved by an institution and how this score is related to the model selected.

In this paper, efficiencies are calculated for a variety of DEA specifications. It is proposed that DEA modelling be embedded in a multivariate statistical framework.

This paper unfolds as follows. The next section contains a discussion of efficiency in financial institutions. The particular case study of Spanish savings banks (Cajas de Ahorros) is introduced and presented in the next section. This is followed by a description of the model and its implementation. The paper is completed with a conclusions section.

2. EFFICIENCY MODELLING IN FINANCIAL INSTITUTIONS

For modelling purposes, financial institutions are seen from the point of view of intermediation or from the point of view of production; see Athanassoupoulos (1997). Under the intermediation model they collect deposits and make loans in order to make a profit.

Deposits and acquired loans are inputs. Institutions are interested in placing loans, which are traditional outputs in studies of this kind; see, for example Berger and Humphrey (1991). Under the production model, a financial institution uses physical resources such as labour and plant in order to process transactions, take deposits, lend funds, and so on. In the production model manpower and assets are treated as inputs and transactions dealt with -such as deposits and loans- are treated as outputs. See, for example, Vassiloglou and Giokas (1990), Schaffnit, Rosen and Paradi (1997), Soteriou and Zenios (1999).

The mathematical models used to study the efficiency of financial institutions can be divided into two groups: those based on parametric frontier techniques, and those based on Data Envelopment Analysis (DEA). Berger and Humphrey find inconsistencies between the two approaches, although Ondrich and Ruggiero (2001) argue that both produce similar rankings, and conclude that there is no advantage in using parametric frontiers.

In this paper we focus on DEA models. Up to what point different DEA modelling approaches produce different results? This question can only be answered by looking at particular case studies. Oral and Yolalan (1990) found that a DEA model aimed at estimating service efficiency in bank branches in Turkey produced indistinguishable results from an alternative DEA model focused on profitability. A way of out this problem, the one implemented in this paper, would be to develop specifications with many inputs and outputs. This would be an attempt to create a general model that encompasses various modelling philosophies as particular cases. But care has to be exercised since the more inputs and outputs a model contains, the more units become efficient through specialisation or, as Lovell and Pastor (1997) put it, “because they are self-identifiers”. The relationship between efficiency and the number of inputs and outputs has been studied by Pedraja Chaparro et al. (1999).

Alternative specifications for inputs and outputs for a given model have been explored in many studies. Athanassopoulos (1997) observes a lack of consistency in the selection of inputs and outputs when studying bank branch efficiency. Oral and Yolalan (1990) experiment with various specifications and observe that efficiencies change according to the input/output mix chosen. Some times there is no choice, as the chosen specification is in part determined by the data that is available; Vassiloglou and Giokas (1990). Pastor and Lovell (1997) observe that alternative specifications may not give significantly different results, and apply the Ruiz Gomez et al. (2002) methodology to choose a parsimonious specification. This approach is based on a sound mathematical model, but has a mechanical feel to it. But different specifications are not totally equivalent, and it is difficult to assess what are the consequences for individual units of adding or removing an input/output without engaging in considerable extra work.

A new approach to specification search is proposed in this paper. The distinctive features of a specification are revealed by embedding DEA efficiency results into a multivariate statistical framework. We use in particular Principal Components Analysis (PCA), multiple regression, and Hierarchical Cluster Analysis (HCA). PCA has been used as an alternative to DEA by Zhu (1998) and Premachandra (2001). PCA as a data reduction technique to select inputs and outputs has been used by Adler and Golany (2001).

In our approach, PCA plays a fundamental role in specification and model selection. We do not attempt to find a "best" specification of inputs and outputs. A variety of possible specifications that offer combinations of inputs and outputs are estimated and efficiencies calculated for each financial institution under each specification. In this way, a matrix is obtained in which each column corresponds to a specification, and each row to a financial institution. This matrix is analysed by means of Principal Components Analysis (PCA). Component scores are plotted to show the extent to which the efficiency of financial institutions remains unchanged under the various specifications. The plot is interpreted by means of property fitting (Pro-Fit), a regression-based technique. The superimposition of the Pro-Fit results on the scores plot will help to identify specification equivalence, guide model selection, identify outlying behaviour, and assess strategic behaviour patterns in financial institutions that achieve the same efficiency score. The methodology will be applied to the particular case of Spanish Savings Banks (Cajas de Ahorro).

3. A CASE STUDY: SPANISH SAVINGS BANKS

Savings banks (Cajas de Ahorro) are key players in the Spanish financial system. They differ from traditional banks in their legal status, which obliges them to invest some of their profits into "good causes" such as supporting the arts or providing for the elderly. Savings banks in Spain tend to operate within specific geographical areas, although some of them have become national institutions. This local character is also reflected in their financial structures, which differ from region to region; see Serrano Cinca (1998) for a discussion of geography and financial success in this context. Wilkinson (2001) points out that Spanish Savings Banks are very successful institutions, with none having defaulted since their creation over a century ago. They take 57% of all deposits, although traditional banks make more loans than they do. In recent years this sector has undergone an intense concentration process. Starting in 1980 there have been 34 mergers. Some other mergers are still under discussion. The largest institutions are Caja Madrid and La Caixa. The total number of Savings Banks is 47. There have been many empirical studies on the efficiency of Spanish financial institutions. Examples are Lozano-Vivas (1997 and 1998), Dietsch and Lozano-Vivas (2000), Lovell and Pastor (1997), Pastor (1999), and Pastor et al (1997).

This section will be divided into sub-sections. First, the data set will be described. The second subheading will concentrate on DEA and PCA. Empirical results will be interpreted in the third and fourth sub-sections.

3.1 THE DATA SET: 3 inputs and 3 outputs

Data was obtained from the Statistic Yearbook of the CECA (The Spanish Confederation of Savings Banks) on annual accounts published by all 47 Spanish Savings Banks for the year 2000. Having been extracted from annual accounts, all the data except number of employees, is measured in monetary units. The list of all institutions is given in Table 1. Rather than use the full name of each institution, the Domain Name of their web page has been employed to identify them. The full Internet address of each institution is of the form www.domainname.es.

After a survey of the inputs and outputs used in the literature, the following inputs and outputs were selected.

Input A: *Number of employees*

Input B: *Fixed assets*

Input C: *Deposits*

Output 1: *Operating Income*

Output 2: *Deposits*

Output 3: *Loans*

There is much agreement on what constitutes inputs and outputs under the production model and under the intermediation model, although not all authors use the same set of inputs and outputs. The list displayed responds to a pragmatic use of available information. A source of debate relates to deposits, which could be seen as inputs or as outputs. See Pastor, Perez and Quesada (1997) for a discussion. Deposits are treated as inputs by Mester (1989), and Elyasiani and Mehdian (1992); they are treated as outputs by Berger and Humphrey (1991), and Ferrier and Lovell (1990); they are treated simultaneously as inputs and outputs by Aly et al (1990). The values of all inputs and outputs for all the Savings Banks are given in Table 1.

Table 1 about here

Notation will be introduced in order to simplify the discussion of the various specifications. Inputs are referred to by means of capital letters, in such a way that the first input is represented by the letter A, the second input by the letter B, and the third one by the letter C. Outputs are referred to by means of numbers. The first input is associated with number 1, the second input with number 2, and the third input with number 3. In this way a specification that treats a savings bank as an institution whose employees (input A) take deposits (output 2) and place loans in the market (output 3) would be labeled A23. If this specification is augmented with fixed assets (input B) and operating income (output 1), the specification becomes AB123. Specification AB123 treats a savings bank as a production unit that employs manpower (A) and plant (B) in order to generate income, deposits, and loans. An intermediation model would be described by a specification such as AC13, in which deposits (C) are treated as an input. Under this specification a savings bank is an institution whose employees collect deposits in order to make loans and generate income.

Other possible views of the way in which a savings bank operates can be generated by using different combinations of inputs and outputs. Efficiency ratios are generated by choosing a specification with only one output and one input. It is, of course, possible to use all possible combinations of inputs with all possible combinations of outputs. The total number of specifications that could possibly be generated with n inputs and m outputs is given by the formula

$$\sum_{i=1}^{n} C_n^i * \sum_{i=1}^{m} C_m^i \quad \text{where } C_n^i = \begin{pmatrix} n \\ i \end{pmatrix} = \frac{n!}{i!\,(n-i)!}$$

In general, it will not be necessary to calculate efficiencies under all possible specifications, as some of them can be discarded on a priori grounds. In our case there are 3 inputs and 3 outputs, giving a possible total number of specifications of 49. Specifications that treat deposits both as inputs and outputs have been excluded, reducing their total number to 33. The complete list of specifications and the inputs and outputs that they contain can be found in Table 2.

Table 2 about here

DEA efficiencies, on a scale from 0% to 100%, for all savings banks were calculated under Constants Returns to Scale (CRS) for all specifications. The results are given in Table 3.

Table 3 about here

Visual examination of Table 3 reveals some important features. Some savings banks (Cajavital, Bbk, Cajamadrid, Cajanavarra, Bancaja) are 100% efficient under many specifications. In the same way, some savings banks achieve low scores under most specifications. No savings banks is efficient under all specifications, highlighting the fact that the selection of inputs and outputs and, therefore, the view of what constitutes efficiency in the financial sector, is a matter of importance. This was one of the conjectures that guided this research. Take, for example, Bbk, which is 100% efficient under 12 specifications, implying that this is an excellent institution. However, its efficiency drops to 52% under B23. This suggests the presence of some weakness in Bbk, a subject that will be further explored below. A counter example is Cajaen, whose DEA scores tend to be low, but becomes 100% efficient under 4 specifications: BC1, BC13, ABC1, ABC13. This indicates that, although Cajaen can take action to improve its efficiency, it has some strong points that deserve further attention.

Consider now the case of two institutions that achieve the same DEA score under a given specification. An example would be Bancaja and Cajavital. They both are 100% efficient under AB123. But differences appear if other specifications are considered. For example, under A123 Cajavital achieves 100% efficiency while the same score for Bancaja is 86%. Under specification B123 Cajavital is 63% efficient while Bancaja is 100% efficient. This indicates that the two institutions follow two different paths to efficiency. What is behind their strategies? Answering such a question was another of the objectives of this research.

In summary, the level of efficiency achieved by a particular financial institution depends on the chosen specification, indicating that specification search is delicate and important. In addition, if two financial institutions achieve the same efficiency score under a given specification they may do so following very different patterns of behavior: there is no single path to efficiency in financial institutions. Exploring what is behind a DEA score is the objective of the next three subsections.

3.2 DEA SPECIFICATION SEARCHES USING MULTIVARIATE METHODS

Although visual inspection of Table 3 is a source of important insights, a more formal analysis of the information it contains will be performed. Table 3 will be treated as a matrix with 47 cases, the savings banks, and 33 variables, the specifications, and analyzed using multivariate statistical methods. The methodological approach will combine PCA, HCA, and Pro-Fit.

The results of applying PCA to Table 3 are shown in Table 4. Four eigenvalues take values larger than one, accounting for 96% of the total variance. The first principal component accounts for 47% of the variance. The second principal component is also of importance, as it accounts for a further 21%. The variance accounted for drops to 18% in the case of the third component, and to 10% in the case of the fourth component. Component loadings are given in Table 5. In what follows the discussion will be based on these four components.

Table 4 about here

Table 5 about here

Component scores were calculated for each savings bank. The plot of the first and second component loadings for each savings bank is shown in Figure 1. The plot of the third and fourth component loadings for each savings bank is shown in Figure 2.

Figure 1 about here

Figure 2 about here

Those savings banks that achieved full 100% efficiency under a majority of specifications (Cajanavarra, Cajamadrid, Cajavital, Kutxa, Bbk) plot towards the right hand side of Figure 1. Those savings banks that consistently underperform plot towards the left hand side of this same figure. It is to be noticed that Caixacarlet, the only institution that no longer exists, having been taken over by Bancaja in July 2001, is located at the extreme of the left hand side. It is, therefore, clear that the first principal component can be interpreted as a "global efficiency score". An efficiency ranking of savings banks can be obtained by simply looking at the ordering on the first component. Usually, efficiency rankings are based on the concept of super-efficiency introduced by Andersen and Petersen (1993), although other ranking methods have also been proposed; Doyle and Green (1994), Sinuany-Stern and Friedman (1998), and Raveh (2000). The advantage of the ranking procedure proposed here is that it embeds results from many different specifications, while the alternatives produce a ranking for each specification.

Concentrating now on the second component, the North-South direction in Figure 1, it can be observed that Bancaja plots towards the top of the figure, while Cajavital plots towards the bottom. Both are 100% efficient under many specifications. In which way they are different, and what accounts for their achieving full efficiency, will be revealed by attaching meaning to the second principal component. In the same way, interpretation of the position of savings banks in Figure 2 requires that meaning be attached to the third and the fourth principal components.

A standard way of attaching meaning to principal components is to analyze component loadings. These are given in Table 5. It can be seen there that all loadings associated with the first component are positive, supporting the view that this component gives an overall measure of efficiency. First component loadings are high for all specifications that exclude input C (deposits). Amongst those specifications that include input C only those which also include inputs A and B achieve high first component loadings. The specifications that achieve the highest first component loadings are AB13, AB123, and AB12. If a combination of inputs and outputs were to be selected in order to produce a global assessment of efficiency, any of these three models would be appropriate.

Specifications that include deposits as an input (C) are salient in the second component, in the sense that they achieve high positive component loadings. The third component appears to be associated with fixed asset utilization (input B), and the fourth one with operating income (output 1).

These results can be visualized by means of Pro-Fit and Cluster analysis. This will be done in the next subsection.

3.3 RESULTS VISUALIZATION AND STRATEGIC PATTERN IDENTIFICATION

Each specification generates a DEA score for each savings bank, and each savings bank is located in Figures 1 and 2 by means of its component scores. The relationship between DEA scores and component scores can be assessed by means of regression analysis and visualized. For each specification, a regression was run in which the dependent variable was the efficiency value, and the independent variables were the four component scores. Each institution was treated as a case in the regression. In total, 33 regressions were performed. This procedure is known as Property Fitting (Pro-Fit) analysis; see Schiffman et al (1981). For a given specification, Pro-Fit produces a directional vector on Figures 1 and 2 in such a way that DEA efficiencies grow in the direction of the vector. Directional vectors were calculated for each one of the 33 specifications. Being regression-based, the quality of the representation can be assessed by means of the coefficient of determination, R^2, and the F statistic. These are shown in Table 6. It is to be noticed that values of R^2 are very high, all of them above 0.90, indicating that there is a strong linear relationship between DEA scores and the position of the savings bank in Figures 1 and 2. The directional vectors are located in Figure 1 and 2 by means of their directional cosines, which are related to the regression coefficients. The value of their standardized directional cosines, -γ_1, γ_2, γ_3, and γ_4- and their level of significance, are also shown in Table 6. Pro-Fit vectors have been superimposed on component plots in Figures 3 and 4.

Table 6 about here

Figure 3 about here

Figure 4 about here

If efficiencies produced by two different specifications are highly correlated, their associated Pro-Fit vectors will plot next to each other. In the same way, if the efficiencies generated by particular specifications are highly correlated with a particular principal component score, the Profit vector will plot in the direction of the axis associated with the given component. The length of the projection of the Pro-Fit vector reflects its relevance in the interpretation of the particular figure. The longer the vector, the more agreement there is between the ordering of the savings banks in the representation and the efficiency values obtained from the specification.

Pro-Fit vectors form a fan in Figure 3. All vectors point in the direction in which efficiency grows. There are 33 specifications, which means that there are 33 definitions of efficiency. Most vectors point in the direction of the first principal component. This confirms the observation that the first principal component gives an overall measure of the efficiency of a savings bank, and that an ordering along the first principal component produces an efficiency ranking of institutions.

A small set of vectors is clearly associated with the second principal component, as they all point towards the top of Figure 3. All such vectors contain deposits as an input, reflecting the fact that the value of the second principal component score is influenced by the decision to model deposits as an input. In other words, amongst the 33 specifications, those that include deposits as an input are a group apart from the rest.

Similar considerations would relate the value of the third principal component to the decision to use specifications that contain as a sole input the value of fixed assets (B), since a fan that includes only B as an input can clearly be discerned on the left hand side of Figure 4.

Finally, in Figure 4 it can be seen that the fourth principal component discriminates between specifications that operating income as an output (output 1) and those that do not contain it. It is clear that vectors that contain output 1 in their definition point towards the bottom of Figure 4, while those that do not contain output 1 in their definition point towards the top of the figure.

All the above discussion has been based on the interpretation of two dimensional projections of a four dimensional data set. Each Pro-Fit vector is plotted in a four dimensional space, and it would be appropriate to assess if the groups that are observed on the projections are true reflections of the groups that exist in the space. For this reason Pro-Fit analysis has been supplemented with Hierarchical Cluster Analysis (HCA). If equivalent specifications exists, they will group into clusters, and if specifications within a cluster share something in common, the analysis will reveal it, with the added bonus that model simplification will naturally follow.

Efficiencies in Table 3 have been taken as inputs for HCA and clustered using Ward's method with Euclidean distances. This method maximizes within group homogeneity and between group heterogeneity. The dendrogram can be seen in Figure 5.

Figure 5 about here

Specifications group neatly into three clusters in Figure 5. These clusters have been superimposed in Figure 3 and have been labeled I, II, and III.

Cluster I is located at the North and North West of Figure 3, grouping specifications whose Pro-Fit vectors point up or up and to the right of the figure. All the specifications in cluster I contain deposits as input (C). It includes specifications of the type C, AC, BC, or ABC. Deposits as an input are a standard feature of intermediation models.

Cluster II is located to the right of Figure 3, above the first principal component. It is formed by specifications that contain a single input, fixed assets (B). Cluster III is located on the right hand side of figure 3, towards the bottom of the first principal component. It groups specifications that do not contain deposits as an input, only A (number of employees) or AB (number of employees and fixed assets). Clusters II and III group specifications that can be associated with production type models. Clusters II and III group together at a higher level of clustering.

It can be argued that specifications contained in a given cluster are largely equivalent in the sense that they produce similar efficiency scores for the various savings banks. This can guide input and output selection. Each cluster can be represented by a single specification, reducing the total number of possible specifications from 33 to 3. The selected specification could be the most parsimonious one or the most central one within the cluster.

The superimposition of HCA and Pro-Fit results on the component score map clearly reveals the differences between the various modeling approaches. The decision to opt for an intermediation model or for a production model, which is related to the way in which deposits are treated in the specification, will impact on the efficiencies obtained for individual saving banks. Since Cluster I is clearly associated with the second principal component and clusters II and III are clearly associated with the first principal component, different views of the world will, in general, lead to different assessments of efficiency and to different calls for action. This leads to the conclusion that if we want to study the efficiency of a savings bank, we should not proceed by choosing only one model and only one specification, as this may miss important features of its operations.

3.4 LOOKING BEYOND THE EFFICIENCY SCORE

It has been argued that there is no single definition of efficiency in the context of savings banks. Different views of the way in which savings banks operate, as reflected in the different modeling philosophies will produce different efficiency scores. The combination of PCA, Pro-Fit, and HCA sheds light into the reasons why a particular savings bank achieves a certain efficiency level. This subject will be further examined in what follows.

Take Bancaja and Cajavital, two previously discussed institutions. They both achieve 100% efficiency under 11 specifications: AB1, AB12, AB123, AB13, AB23, AB3, AC13, AC3, ABC1, ABC13 and ABC3. They both appear on the extreme right hand side of the first principal component in Figure 1. They would both come at the top of an efficiency ranking based on the first principal component. We could just conclude that they are excellent institutions and leave it at that. But it is also to be noticed that under specifications A1, A12, A123, A13, A23, A2, A3, and AB2 Cajavital is 100% efficient but not Bancaja. The Pro-Fit lines associated with all these specifications point towards the negative of the second principal component in Figure 3. All these specifications contain number of employees (A) in their definition, which leads to the conclusion that Cajavital owes its position in the league table to the good performance of its employees. The specifications that make Bancaja is 100% efficient but not Cajavital can be divided into two groups. The first group contains C13, C3, BC13, BC1, and BC3 whose associated Pro-Fit lines point directly upwards, in the direction of the second principal component. All these contain Deposits as an input, and are specifications that would be developed under the intermediation modeling philosophy. The second group contains specifications B1, B12, B123, B13, B23, and B3, all of them belonging to Cluster II and containing fixed assets (B) in their definition. One can conclude that Bancaja's strong point is an efficient utilization of its fixed assets, and that Bancaja is a good institution from the intermediation point of view.

This discussion can be extended to the differences and similarities of Bancaja and Cajavital under the third and fourth principal components. Cajavital is located on the positive side of the third principal component, while Bancaja is located on the negative side of this component. Recall that the third principal component is associated with fixed assets (input B), we observe that the use of fixed assets discriminates between the two institutions, a conclusion that has already been arrived at by means of Cluster analysis. The fourth principal component, associated with operating income (output 1), shows little difference between these two savings banks.

Systematic analysis of Figures 1 and 2, together with the interpretations provided in Figures 3 and 4 makes it possible to assess the global efficiency of an institution and the strategies under which such global efficiency was achieved. Strengths and weaknesses become apparent. Take, for example, a previously mentioned case: Cajaen. In Figure 1 it plots towards the center of the first component, indicating that its global efficiency is mediocre. In is also located at the top of the second principal component, which is associated with is consistent with being 100% efficient under specifications BC1, BC13, ABC1, and ABC13, all of them belonging to Cluster I and considering deposits as an input, and implying that Cajaen would be only identified as efficient under an intermediation approach. In Figure 2 Cajaen is located towards the most negative side of the fourth principal component. Cajaen would be identified as strong in specifications that include operating income as an output. Finally, Bbk, appears on the extreme right hand side of the Figure 1, implying that it is an efficient savings bank from the global point of view. Its location in this figure is consistent with an efficient use of human resources (input A). In Figure 2, Bbk is also located towards the extreme right hand side, on the lower half of the figure. We notice that in Figure 4, vectors associated with specifications that contain fixed assets (input B) point on the whole towards the left hand side. This implies that Bbk under performs in specifications that contain fixed assets as an input, something that is coherent with the results shown in Table 3.

4 CONCLUSIONS

There has been much interest and debate on how to model DEA efficiency in financial institutions. This has extended over the type of model (intermediation or production) that is appropriate, as well as to the selection of inputs and outputs once a modeling philosophy has been selected. We have suggested a specification search strategy that highlights the extent to which two different DEA specifications produce similar results and the reasons why this happens.

The methodology proposed relies on estimating a variety of input/output mixtures and analyzing the results by means of multivariate statistical methods. Particular emphasis is given to data visualization, which is achieved by combining Principal Components Analysis, Property Fitting, and Hierarchical Cluster Analysis.

This approach has been applied to the particular case of Spanish savings banks. Three different views of what constitutes efficiency in a savings bank have been identified, although these can be further grouped into two that are related to the intermediation and the production models. The treatment of deposits as an input or as an output has proven to be key in the modeling of financial institutions.

The standard procedure of starting by an a priori view of what inputs and outputs should go into the calculation of efficiency should be revised, as different models and specifications can produce different efficiency results for a given institution. A more realistic view would be to accept that efficiency is a multidimensional concept, and that several models ought to be estimated and combined before managerial action is taken to improve the way in which a financial institution works.

Framing DEA results in a multivariate statistical context has allowed us to go behind efficiency as a mere score. It has been possible to offer a global view of the efficiency of an institution which encompasses many specifications; it has made it possible to assess why a particular institution has achieved a given level of efficiency under a given choice of inputs and outputs; and has allowed to identify the various paths to efficiency followed by different institutions which would, under most studies, have been classified as equivalent but that differ in important aspects of their operations.

Further advantages of the method proposed here is that it creates a natural ranking of institutions in terms of efficiency, and that it highlights the strengths and weaknesses of each institution.

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Savings Bank	*Number of employees*	*Fixed assets*	*Operating income*	*Deposits*	*Loans*
Bancaja	4,551	37,346	97,758	1,907,234	2,147,534
Bbk	2,511	50,694	73,195	1,666,972	1,088,115
Cai	1,225	16,940	29,548	503,394	478,491
Caixacarlet	83	1,126	952	20,844	20,789
Caixacatalunya	4,801	78,376	93,586	2,486,395	2,276,395
Caixagalicia	3,425	49,775	76,554	1,660,766	1,305,776
Caixagirona	756	6,952	13,776	382,213	241,493
Caixalaietana	773	18,886	13,124	316,066	262,953
Caixamanlleu	380	4,414	6,312	137,480	105,931
Caixamanresa	583	4,893	11,848	267,540	188,761
Caixanova	2,299	32,465	50,584	1,027,050	787,264
Caixaontinyent	218	2,288	2,916	57,378	61,413
Caixapenedes	1,903	35,147	33,188	798,094	715,034
Caixasabadell	1,245	13,951	19,785	466,732	456,653
Caixatarragona	1,164	8,347	18,536	446,508	339,479
Caixaterrassa	1,090	8,884	17,689	416,881	317,650
Cajabadajoz	770	11,030	13,089	244,019	190,024
Cajacanarias	1,044	9,948	25,121	504,200	408,342
Cajacantabria	998	14,265	21,233	434,818	337,316
Cajacirculo	550	12,800	12,613	289,777	153,653
Cajadeavila	578	7,622	12,558	231,719	181,912
Cajadeburgos	753	14,732	18,288	502,969	371,792
Cajaduero	2,459	41,204	38,291	1,203,134	740,224
Cajaen	133	1,130	2,154	37,180	33,609
Cajaespana	2,666	48,512	58,120	1,275,801	976,839
Cajaextremadura	1,063	10,269	17,335	401,218	282,454
Cajagranada	2,049	24,293	32,848	690,784	649,897
Cajaguadalajara	233	2,242	3,460	82,167	69,047
Cajamadrid	10,952	205,193	300,763	6,287,709	5,981,043
Cajamurcia	1,510	20,055	34,940	785,773	622,753
Cajanavarra	1,369	13,398	31,529	841,902	668,661
Cajarioja	411	5,422	7,077	176,630	176,420
Cajasanfernando	2,084	21,750	30,750	605,413	569,226
Cajasegovia	524	9,896	10,522	237,869	211,685
Cajastur	1,324	16,302	32,608	756,633	526,704
Cajasur	2,210	31,473	40,019	912,072	841,895
Cajavital	672	12,961	19,612	504,555	370,498
Cam	5,031	59,676	97,589	2,106,343	2,022,398
Ccm	2,179	31,808	37,089	936,451	676,599
Colonya	63	716	1,030	23,857	18,896
Elmonte	1,982	24,431	38,309	744,619	787,766
Ibercaja	4,241	43,135	68,216	1,789,422	1,478,053
Kutxa	1,654	38,807	47,738	1,100,332	807,668
Lacaixa	19,126	330,404	401,928	7,885,253	7,199,949
Lacajadecanarias	931	13,351	19,492	402,543	340,800
Sanostra	1,412	18,545	22,935	557,223	492,561
Unicaja	4,510	59,741	77,010	1,596,091	1,238,335

Table 1: List of savings banks and the values of inputs and outputs.

Model	*INPUT*	*OUTPUT*
A1	Employees	Income
A12	Employees	Income, Deposits
A123	Employees	Income, Deposits, Loans
A13	Employees	Income, Loans
A23	Employees	Deposits, Loans
A2	Employees	Deposits
A3	Employees	Loans
B1	Assets	Income
B12	Assets	Income, Deposits
B123	Assets	Income, Deposits, Loans
B13	Assets	Income, Loans
B23	Assets	Deposits, Loans
B2	Assets	Deposits
B3	Assets	Loans
AB1	Employees, Assets	Income
AB12	Employees, Assets	Income, Deposits
AB123	Employees, Assets	Income, Deposits, Loans
AB13	Employees, Assets	Income, Loans
AB23	Employees, Assets	Deposits, Loans
AB2	Employees, Assets	Deposits
AB3	Employees, Assets	Loans
C1	Deposits	Income
C13	Deposits	Income, Loans
C3	Deposits	Loans
AC1	Employees, Deposits	Income
AC13	Employees, Deposits	Income, Loans
AC3	Employees, Deposits	Loans
BC1	Assets, Deposits	Income
BC13	Assets, Deposits	Income, Loans
BC3	Assets, Deposits	Loans
ABC1	Employees, Assets, Deposits	Income
ABC13	Employees, Assets, Deposits	Income, Loans
ABC3	Employees, Assets, Deposits	Loans

Table 2: The 33 specifications and their definitions

	A1	A12	A123	A13	A23	A2	A3	B1	B12	B123	B13	B23	B2	B3	AB1	AB12	AB123	AB13	AB23	AB2	AB3	C1	C13	C3	AC1	AC13	AC3	BC1	BC13	BC3	ABC1	ABC13	ABC3
Bancaja	74	74	86	86	86	56	86	100	100	100	100	100	81	100	100	100	100	100	100	81	100	87	100	100	88	100	100	100	100	100	100	100	100
Bbk	100	100	100	100	88	88	79	55	58	58	55	52	52	37	100	100	100	100	88	88	79	75	75	58	100	100	79	76	76	58	100	100	79
Cai	83	83	83	83	71	55	71	67	67	67	67	52	47	49	92	92	92	92	76	61	76	100	100	84	100	100	84	100	100	84	100	100	84
Caixacarlet	39	39	45	45	45	33	45	32	34	34	32	34	29	32	44	44	49	49	49	38	49	78	89	89	78	89	89	78	89	89	78	89	89
Caixacatalunya	67	69	86	86	86	69	86	46	51	55	51	55	50	51	71	71	89	89	89	73	89	64	81	81	74	91	91	65	81	81	74	91	91
Caixagalicia	77	77	77	77	69	65	69	59	61	61	59	53	53	46	84	84	84	84	73	71	73	79	80	70	87	87	76	80	81	70	88	88	76
Caixagirona	62	67	67	62	67	67	58	76	87	87	76	87	87	60	78	78	87	78	87	87	66	61	63	56	70	70	62	76	76	60	78	78	66
Caixalaietana	58	58	62	62	62	54	62	27	28	28	27	27	27	24	58	58	62	62	62	54	62	71	78	74	71	78	74	71	78	74	71	78	74
Caixamanlleu	57	57	57	57	51	48	51	55	57	57	55	50	50	42	66	66	66	66	56	56	56	78	79	68	78	79	68	79	79	68	79	79	68
Caixamanresa	70	70	70	70	61	61	59	93	97	97	93	87	87	67	93	93	97	93	87	87	68	75	75	63	81	81	66	93	93	67	93	93	68
Caixanova	75	75	75	75	62	60	62	60	60	60	60	50	50	42	83	83	83	83	66	66	66	84	84	68	89	89	71	85	85	68	89	89	71
Caixaontinyent	46	46	51	51	51	35	51	49	49	49	49	48	40	47	54	54	57	57	57	42	57	87	97	95	87	97	95	87	97	95	87	97	95
Caixapenedes	60	60	68	68	68	56	68	36	39	39	36	39	36	35	61	61	69	69	69	57	69	71	80	80	72	80	80	71	80	80	72	80	80
Caixasabadell	54	54	67	67	67	50	67	54	58	60	57	60	53	57	64	64	74	74	74	59	74	72	87	87	72	87	87	74	87	87	74	87	87
Caixatarragona	55	55	55	55	53	51	53	85	91	91	85	85	85	71	85	85	91	85	85	85	71	71	75	68	71	75	68	85	85	71	85	85	71
Caixaterrassa	56	56	56	56	53	51	53	76	81	81	76	75	75	62	76	76	81	76	75	75	62	72	75	68	72	75	68	81	81	68	81	81	68
Cajabadajoz	58	58	58	58	45	42	45	45	45	45	45	35	35	30	64	64	64	64	48	47	48	91	91	69	91	91	69	91	91	69	91	91	69
Cajacanarias	82	82	82	82	71	64	71	96	97	97	96	82	81	71	100	100	100	100	82	81	81	85	85	72	94	94	78	97	97	72	100	100	81
Cajacantabria	73	73	73	73	61	58	61	57	58	58	57	49	49	41	80	80	80	80	65	64	65	83	83	69	86	86	70	83	83	69	87	87	70
Cajacirculo	79	79	79	79	70	70	51	38	40	40	38	36	36	21	79	79	79	79	70	70	51	74	74	47	87	87	53	74	74	47	87	87	53
Cajadeavila	74	74	74	74	57	53	57	63	63	63	63	48	48	42	84	84	84	84	62	60	62	92	92	70	92	92	70	93	93	70	93	93	70
Cajadeburgos	83	89	90	90	90	89	90	47	54	54	47	54	54	44	83	83	90	90	90	89	90	62	68	66	83	90	90	64	68	66	84	90	90
Cajaduero	53	65	65	55	65	65	55	36	46	46	36	46	46	31	56	56	68	56	68	68	56	54	59	55	61	62	60	54	59	55	61	62	60
Cajaen	55	55	55	55	46	37	46	73	73	73	73	56	52	52	73	73	73	73	56	52	53	99	99	80	99	99	80	100	100	80	100	100	80
Cajaespana	75	75	75	75	66	64	66	46	48	48	46	42	42	35	76	76	76	76	67	65	67	78	79	68	85	85	73	78	79	68	85	85	73
Cajaextremadura	56	56	56	56	50	50	48	64	68	68	64	62	62	48	68	68	69	68	62	62	55	74	74	63	74	74	63	79	79	63	79	79	63
Cajagranada	55	55	58	58	58	45	58	52	53	53	52	50	45	47	63	63	65	65	63	52	63	81	88	84	81	88	84	81	88	84	81	88	84
Cajaguadalajara	51	51	54	54	54	47	54	59	63	63	59	60	58	54	62	62	64	64	61	58	61	72	79	75	72	79	75	75	79	75	76	79	75
Cajamadrid	94	94	99	99	99	76	99	56	57	57	56	54	49	51	95	95	100	100	100	77	100	81	89	84	100	100	100	82	89	84	100	100	100
Cajamurcia	79	79	79	79	75	69	75	67	70	70	67	62	62	54	89	89	89	89	81	78	81	76	79	70	88	88	79	81	81	70	91	91	81
Cajanavarra	79	82	89	89	89	82	89	90	100	100	90	100	100	87	95	95	100	100	100	100	100	64	72	71	82	89	89	90	90	87	95	100	100
Cajarioja	59	59	78	78	78	57	78	50	54	59	57	59	52	57	66	66	84	84	84	65	84	68	89	89	70	90	90	69	89	89	71	90	90
Cajasanfernando	51	51	51	51	50	39	50	54	54	54	54	49	44	46	60	60	61	61	55	47	55	87	92	84	87	92	84	87	92	84	87	92	84
Cajasegovia	69	69	73	73	73	60	73	41	43	43	41	41	38	37	69	69	74	74	74	61	74	75	83	79	80	86	83	75	83	79	80	86	83
Cajastur	84	84	84	84	76	76	72	76	81	81	76	74	74	56	96	96	97	96	88	88	79	73	73	62	90	90	73	82	82	62	96	96	79
Cajasur	62	62	69	69	69	55	69	49	51	51	49	50	46	47	68	68	74	74	74	61	74	75	84	82	75	84	82	75	84	82	75	84	82

Cajavital	100	100	100	100	100	100	100	58	63	63	58	62	62	50	100	100	100	100	100	100	100	66	71	65	100	100	100	71	71	65	100	100	100
Cam	66	66	73	73	73	56	73	62	65	65	62	63	56	59	77	77	80	80	80	65	80	79	88	85	80	88	85	82	88	85	83	88	85
Ccm	58	58	58	58	57	57	56	45	49	49	45	47	47	37	64	64	65	64	63	63	60	67	71	64	69	72	65	67	71	64	69	72	65
Colonya	56	56	56	56	54	50	54	55	58	58	55	53	53	46	65	65	66	66	60	59	60	74	78	70	74	78	70	75	78	70	76	78	70
Elmonte	66	66	72	72	72	50	72	60	60	60	60	57	49	56	76	76	79	79	79	58	79	88	97	94	88	97	94	88	97	94	88	97	94
Ibercaja	55	56	63	63	63	56	63	60	67	67	60	67	66	60	66	66	71	71	71	68	71	65	74	73	66	74	74	71	74	73	71	74	74
Kutxa	99	99	99	99	89	89	89	47	50	50	47	45	45	36	99	99	99	99	89	89	89	74	75	65	99	100	89	74	75	65	99	100	89
Lacaixa	72	72	72	72	68	55	68	46	47	47	46	41	38	38	75	75	75	75	70	57	70	87	91	81	87	91	81	87	91	81	87	91	81
Lacajadecanarias	72	72	72	72	66	58	66	56	57	57	56	50	48	44	79	79	79	79	71	64	71	82	85	75	85	87	77	83	85	75	85	87	77
Sanostra	56	56	63	63	63	53	63	47	51	51	47	51	48	46	63	63	68	68	68	60	68	70	79	79	70	79	79	70	79	79	70	79	79
Unicaja	59	59	59	59	50	47	50	49	50	50	49	43	43	36	66	66	66	66	54	53	54	82	82	69	82	82	69	82	82	69	82	82	69

Table 3. Efficiency results under all specifications

Component	*Eigenvalue*	*% of variance*	*Cumulative*
PC1	15.596	47.261	47.261
PC2	7.012	21.248	68.509
PC3	5.962	18.067	86.576
PC4	3.416	10.351	96.926
PC5	.475	1.440	98.366
PC6	.188	.570	98.936
PC7	.107	.324	99.260

Table 4. PCA results.

	PC1	*PC2*	*PC3*	*PC4*
A1	.828	-.279	.363	-.298
A12	.819	-.350	.342	-.264
A123	.849	-.289	.403	-
A13	.858	-.234	.421	-
A23	.790	-.321	.397	.303
A2	.717	-.644	.238	-
A3	.790	-.186	.413	.386
B1	.640	.296	-.701	-
B12	.637	.174	-.748	-
B123	.640	.174	-.744	-
B13	.647	.298	-.696	-
B23	.622	-	-.729	.251
B2	.603	-	-.772	.147
B3	.598	.333	-.602	.394
AB1	.945	-	-	-.282
AB12	.945	-	-	-.282
AB123	.961	-.166	-	-
AB13	.975	-	-	-
AB23	.883	-.249	-	.333
AB2	.824	-.494	-.232	-
AB3	.857	-	.195	.448
C1	-	.809	.184	-.521
C13	-	.927	.294	-
C3	-	.786	.260	.536
AC1	.591	.346	.432	-.547
AC13	.577	.527	.559	-.145
AC3	.448	.442	.503	.547
BC1	.340	.781	-.240	-.426
BC13	.217	.940	-	-
BC3	-	.781	.169	.582
ABC1	.751	.365	.115	-.488
ABC13	.724	.513	.302	-.173
ABC3	.524	.424	.414	.557

Tabla 5. Component score matrix

Model	Directional cosines				F	Adj R2
	g_1	g_2	g_3	g_4		
A1	0.83 (43.59)**	-0.28 (-14.66)**	0.37 (19.12)**	-0.30 (-15.68)**	681.8	0.98
A12	0.83 (37.99)**	-0.35 (-16.23)**	0.35 (15.86)**	-0.27 (-12.26)**	527.2	0.98
A123	0.86 (30.38)**	-0.29 (-10.33)**	0.41 (14.43)**	-0.01 (-0.40)	309.5	0.96
A13	0.87 (31.56)**	-0.24 (-8.59)**	0.43 (15.49)**	-0.02 (-0.79)	327.5	0.97
A23	0.80 (33.13)**	-0.32 (-13.44)**	0.40 (16.66)**	0.31 (12.72)**	429.3	0.97
A2	0.72 (38.55)**	-0.65 (-34.59)**	0.24 (12.82)**	0.00 (0.14)	711.6	0.98
A3	0.80 (35.11)**	-0.19 (-8.27)**	0.42 (18.36)**	0.39 (17.17)**	483.1	0.98
B1	0.64 (51.97)**	0.30 (24.03)**	-0.70 (-56.89)**	-0.07 (-5.58)**	1636.5	0.99
B12	0.64 (56.12)**	0.17 (15.31)**	-0.75 (-65.91)**	0.00 (-0.13)	1931.9	0.99
B123	0.64 (54.95)**	0.17 (14.95)**	-0.75 (-63.88)**	0.03 (2.30)*	1832.3	0.99
B13	0.65 (48.18)**	0.30 (22.24)**	-0.70 (-51.85)**	-0.03 (-2.55)*	1377.7	0.99
B23	0.63 (38.61)**	0.09 (5.41)**	-0.73 (-45.20)**	0.25 (15.59)**	951.5	0.99
B2	0.61 (30.97)**	-0.05 (-2.70)**	-0.78 (-39.69)**	0.15 (7.56)**	649.8	0.98
B3	0.60 (32.32)**	0.34 (18.03)**	-0.61 (-32.53)**	0.40 (21.33)**	720.7	0.98
AB1	0.95 (47.07)**	-0.08 (-4.09)**	-0.06 (-2.77)**	-0.28 (-14.05)**	609.3	0.98
AB12	0.95 (47.07)**	-0.08 (-4.09)**	-0.06 (-2.77)**	-0.28 (-14.05)**	609.3	0.98
AB123	0.98 (31.72)**	-0.17 (-5.47)**	-0.08 (-2.54)*	-0.07 (-2.29)*	262.0	0.96
AB13	0.99 (33.89)**	-0.09 (-3.14)**	0.02 (0.76)	-0.08 (-2.67)*	291.6	0.96
AB23	0.90 (26.31)**	-0.25 (-7.42)**	-0.03 (-0.94)	0.34 (9.91)**	211.6	0.95
AB2	0.83 (37.29)**	-0.50 (-22.34)**	-0.23 (-10.50)**	0.05 (2.20)*	501.1	0.98
AB3	0.87 (38.96)**	-0.08 (-3.50)**	0.20 (8.86)**	0.45 (20.36)**	505.8	0.98
C1	0.04 (1.26)	0.82 (26.64)**	0.19 (6.06)**	-0.53 (-17.17)**	260.7	0.96
C13	0.00 (0.07)	0.95 (26.47)**	0.30 (8.39)**	-0.05 (-1.50)	193.3	0.94
C3	-0.03 (-1.08)	0.80 (30.61)**	0.26 (10.14)**	0.54 (20.87)**	369.1	0.97
AC1	0.60 (18.09)**	0.35 (10.60)**	0.44 (13.24)**	-0.56 (-16.74)**	223.8	0.95
AC13	0.59 (15.94)**	0.54 (14.55)**	0.58 (15.45)**	-0.15 (-4.01)**	180.2	0.940
AC3	0.46 (12.76)**	0.45 (12.57)**	0.52 (14.30)**	0.56 (15.58)**	192.0	0.94
BC1	0.35 (11.59)**	0.80 (26.66)**	-0.24 (-8.18)**	-0.43 (-14.53)**	280.9	0.96
BC13	0.22 (5.71)**	0.97 (24.74)**	-0.05 (-1.27)	-0.08 (-2.06)*	162.6	0.93
BC3	0.05 (2.26)*	0.79 (35.07)**	0.17 (7.58)**	0.59 (26.12)**	493.7	0.98
ABC1	0.77 (21.26)**	0.37 (10.32)**	0.12 (3.26)**	-0.50 (-13.80)**	189.9	0.94
ABC13	0.76 (15.58)**	0.54 (11.03)**	0.32 (6.50)**	-0.18 (-3.72)**	105.1	0.90
ABC3	0.54 (13.39)**	0.44 (10.85)**	0.43 (10.60)**	0.58 (14.24)**	153.1	0.93

** Significant at the 0.01 level. * Significant at the 0.05 level

Table 6. Pro-Fit Analysis. Linear regression results

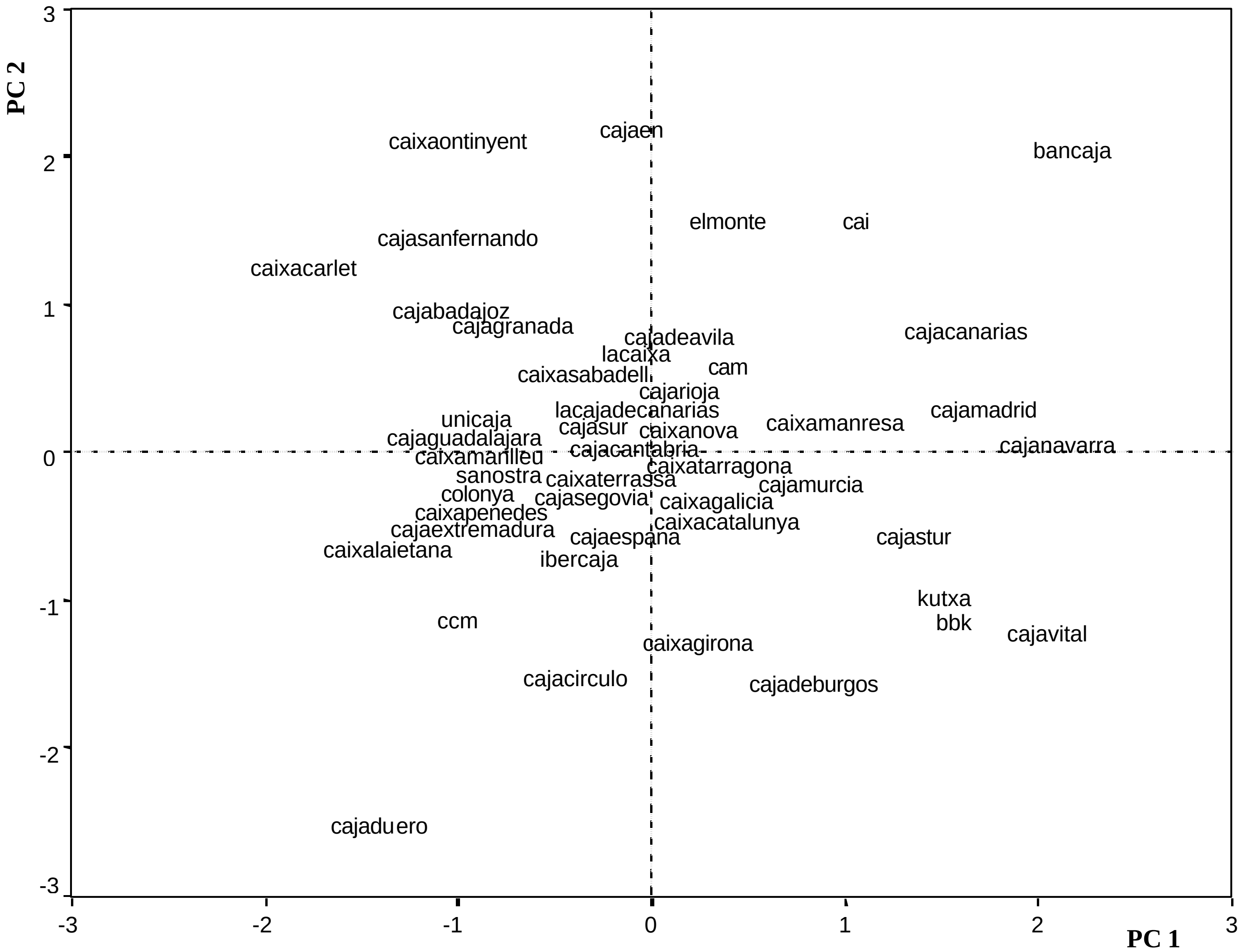

Figure 1. Plot of the first and the second principal component scores

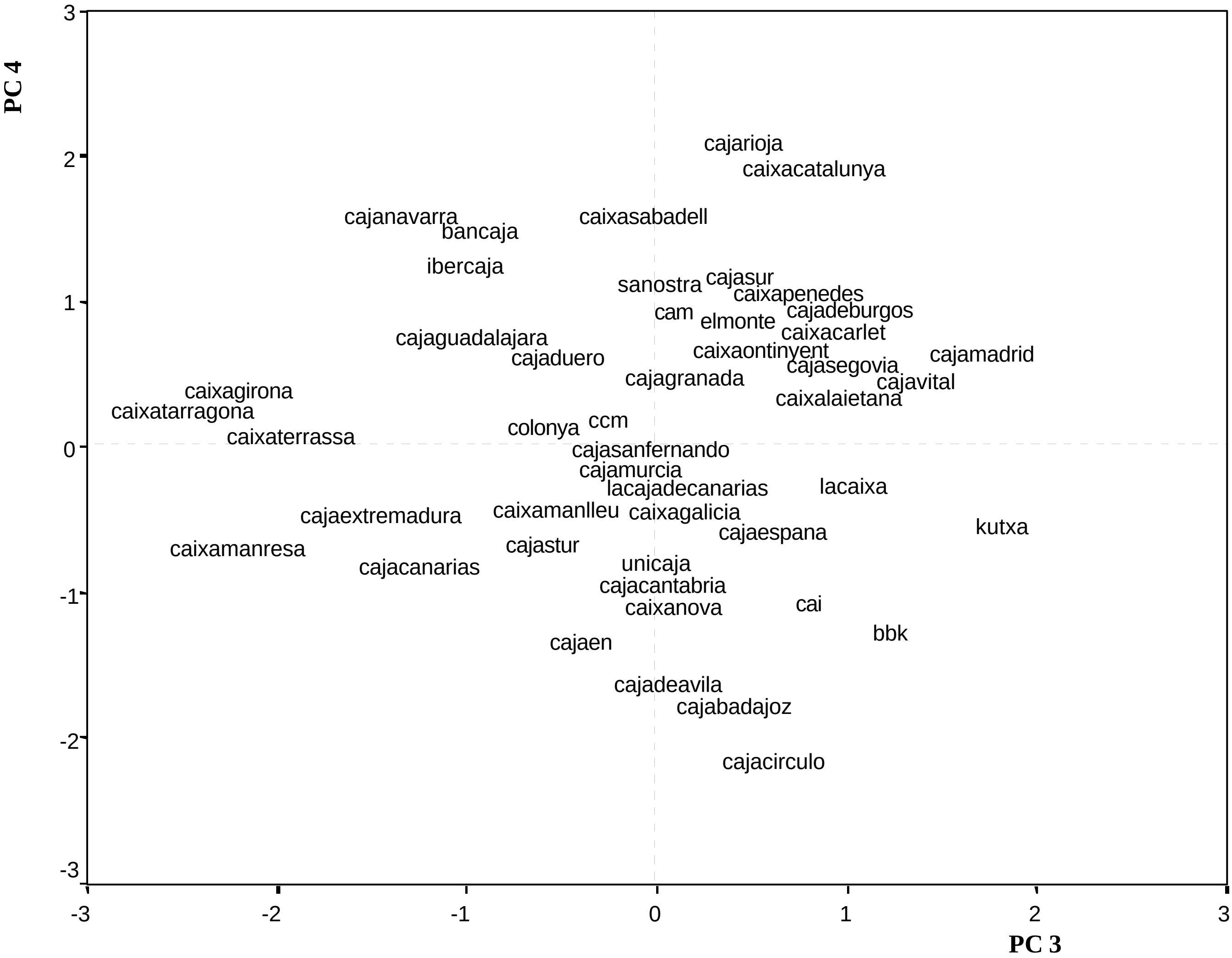

Figure 2. Plot of the third and the fourth principal component scores

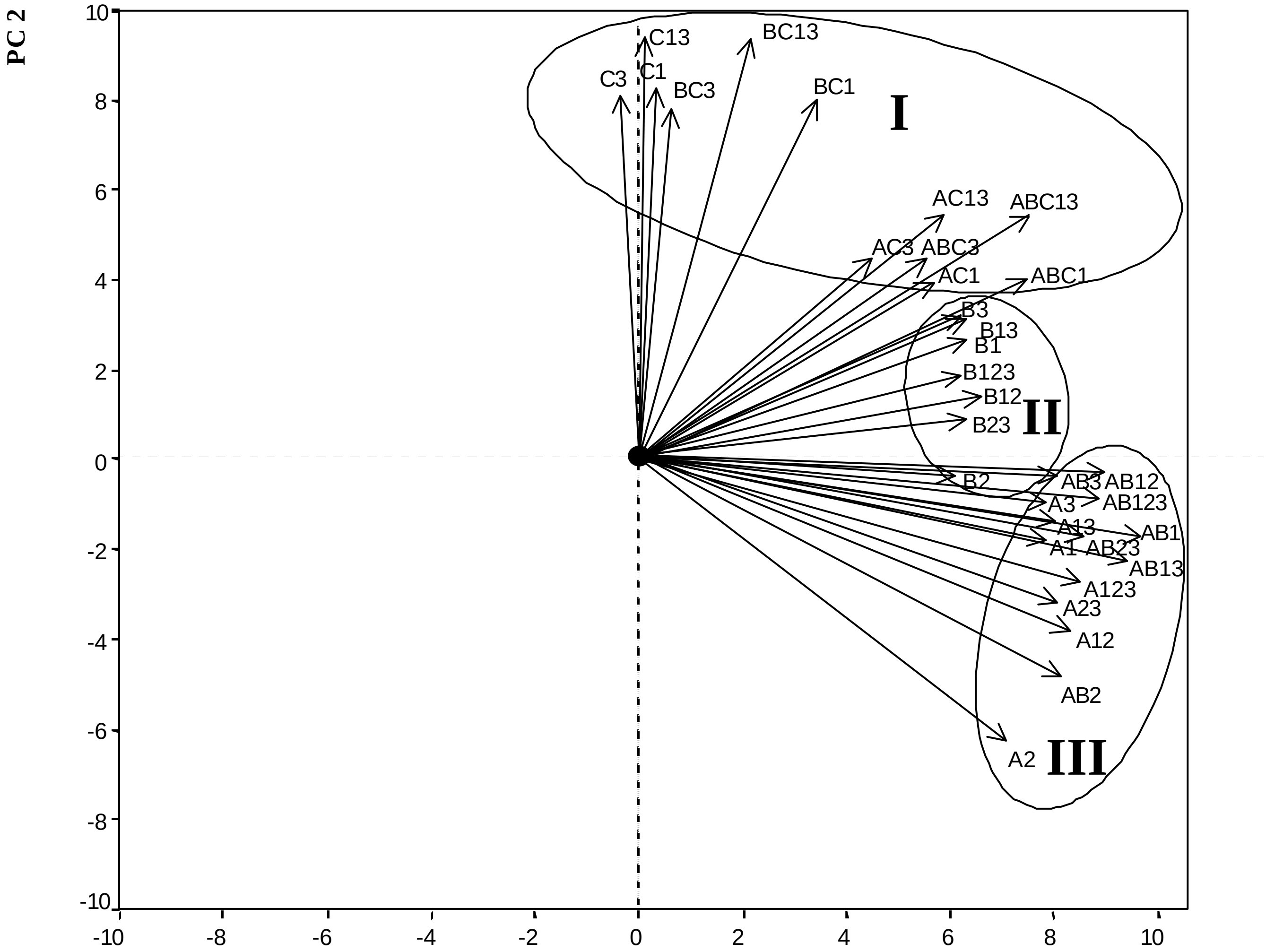

Figure 3. Pro-Fit lines and cluster results in the first two component plot.

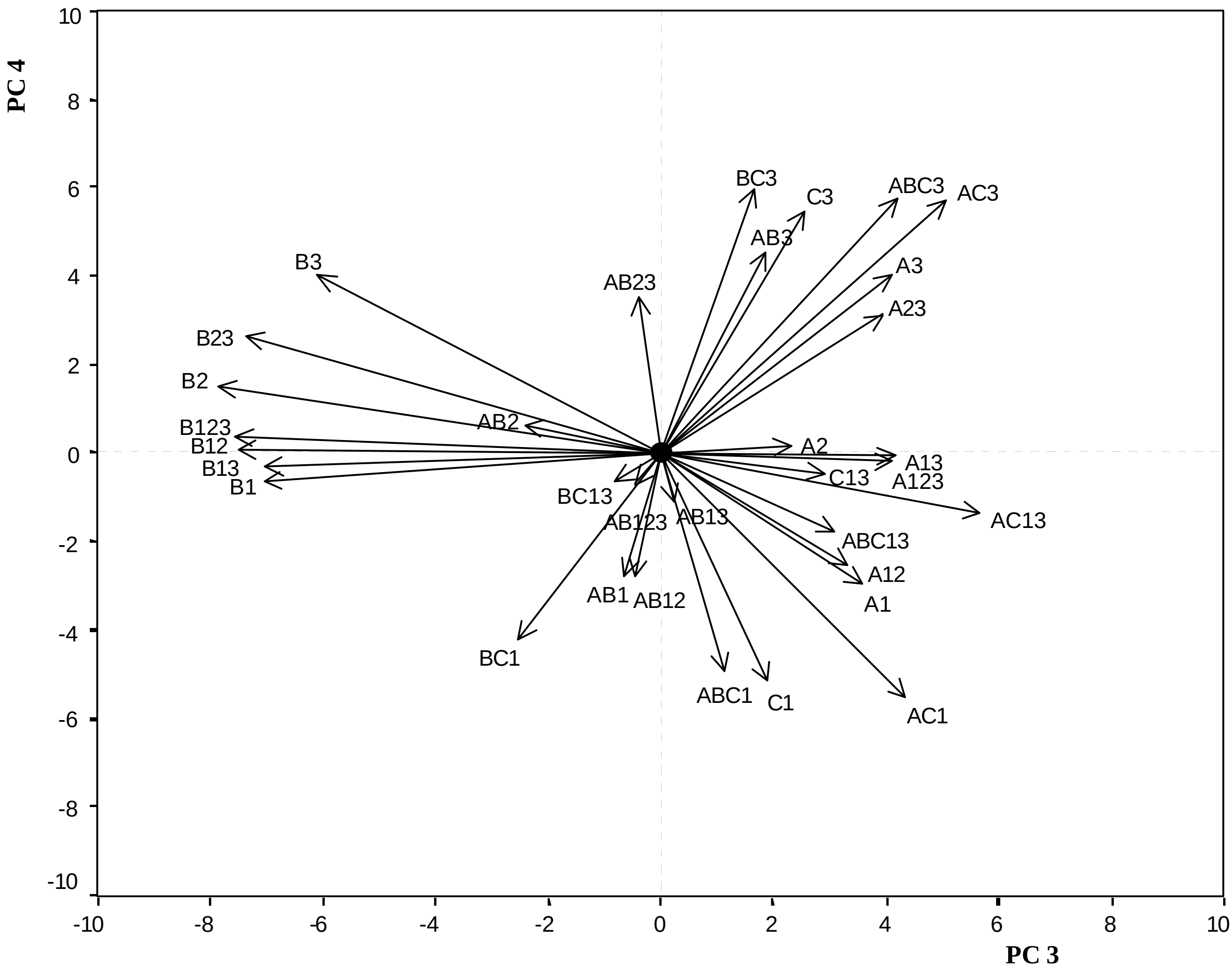

Figure 4. Pro-Fit results on the third and the fourth components plot

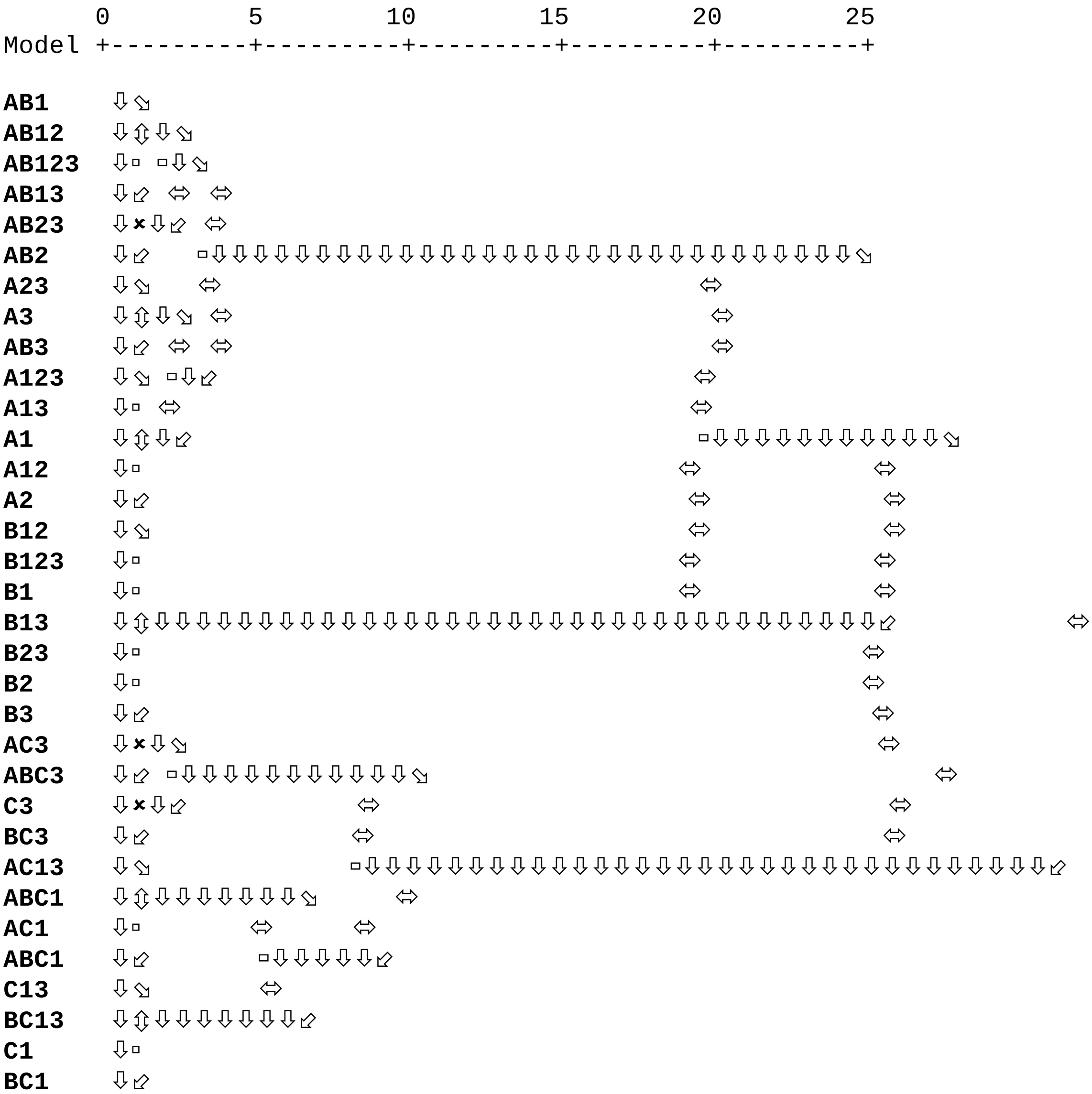

Figure 5. Ward's method. Dendrogram.