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What about the social efficiency in credit cooperatives? Evidence from Spain (2008-2014)

Abstract Credit cooperatives are financial intermediaries that pay attention to social criteria. Thus, if such entities want to survive and thrive in the new international context, they cannot ignore their inefficiencies in both the financial and social dimensions of their activity. However, previous research on efficiency in credit cooperatives is very limited and only considers their financial activity. To date, no study has been published giving evidence through indicators on whether these banking institutions are socially efficient. This paper therefore constructs a social efficiency index of Spanish credit cooperatives during the period 2008-2014 and examines its main explanatory factors. After applying a two-stage Data Envelopment Analysis (DEA) approach, the results from the first stage indicate that, on average, the social efficiency of Spanish credit cooperatives reaches an acceptable level of 66.42%. Second-stage truncated regression reveals that entities with a greater proportion of branches in urban areas are socially less efficient, whereas both their size and the number of service points have a positive effect. Interestingly, social efficiency also varies significantly depending on the regional location of credit cooperatives in Spain. As a result, our findings enable these Social Economy financial institutions to both know their performance relative to their social activity and use this information to improve their competitiveness in the future.

Key words Social efficiency; Credit cooperatives; Spain; DEA approach; Truncated regression

1 Introduction

Social enterprises are increasingly attracting the attention of scholars and practitioners today owing to the growing demand for business organizations to trigger positive social change (Pache and Santos 2013; Battilana and Lee 2014; Miles et al. 2014; Battilana et al. 2015; Ramus and Vaccaro 2015). This is turning out to be especially relevant in the financial sector, where the abuses and limitations of traditional commercial banks are leading to the development of what are known as "*Social Economy financial institutions*" (Cornée and Szafarz 2014; Gutiérrez-Nieto et al. 2015; Jackson 2015).

Specifically, among the different Social Economy financial institutions, credit cooperatives are becoming more and more popular in numerous developed countries such as United States, Canada, Australia, Japan, France, Germany and Italy, among many others. These entities are self-help cooperative financial organizations geared to attaining the economic and social goals of their members and wider local communities (McKillop and Wilson 2011). Their importance lies not in their weight in the financial system of such countries but in the type of activity they perform, financing a large set of social enterprises and helping to support employment and growth in the location where they work (Glass et al. 2014). Moreover, credit cooperatives also contribute to the development of the financial sector by meeting some needs that are not covered by other banking intermediaries and by increasing free competition within it (Kalmi 2012). These entities therefore are hybrid organisations (Server and Capó-Vicedo 2011; Ory and Lemzeri 2012): on the one hand, they are cooperatives established for an important social function and, on the other hand, they are entities in the financial system alongside banks and savings banks. However, the social mission of credit cooperatives is the main reason for their existence.

In Spain, in application of Law 13/1989 of 26 May on Credit Cooperatives, the National Union of Spanish Credit Cooperatives (Unión Nacional de Cooperativas de Crédito Españolas, UNACC) defines these entities as "*cooperative societies with their own legal status, whose social purpose is to meet the financial needs of their members and of third parties by performing activities related to credit entities*". Thus, being organizations that do not follow profit maximization, their main aim is to improve the economic and social welfare of their members, while the members' objective is to use financial services and not to obtain dividends.

Unlike the traditional commercial banking institutions, Spanish credit cooperatives are independent, solid, and viable financial entities which have remained practically unaffected by the recent crisis. Indeed, in general they have met the capitalization and solvency requirements imposed by the European Union, and none of them have either needed to be bailed out or received State funding. In addition, although an intensive restructuring process is under way, this has been done voluntarily and with the aim of making them more efficient and competitive in their financial activity (Zvolská and Olsson 2012). But have Spanish credit cooperatives been socially efficient during the crisis period? This is the question that this study seeks to address.

The social efficiency of credit cooperatives has to do with how effectively these entities meet the social objectives of their members and local community (Ory and Lemzeri 2012). However, social efficiency is rarely pursued by credit cooperatives as part of a deliberate and managed strategy. As a result, in contrast to financial efficiency, there is no empirical research, either national or international, measuring whether these entities are socially efficient. Unfortunately, there is also no academic contribution on the explanatory factors of their social efficiency. But beyond financial performance, credit cooperatives are also to be assessed with regard to their social impact. As with financial goals, it is likely that these entities can more successfully achieve social goals if they know their progress towards them. Consequently, credit cooperatives' social efficiency needs to be measured by an indicator to both determine the performance of these entities relative to their social mission and use this information to improve their global performance and competitiveness in the new international context (Kalmi 2012).

This study therefore has two purposes: first, to estimate the relative level of social efficiency in Spanish credit cooperatives during the period 2008-2014, and second, to analyse the determinants of social efficiency. In order to accomplish these purposes, we use the two-stage Data Envelopment Analysis (DEA) approach developed by Simar and Wilson (2007). In the first stage, relative efficiency scores are calculated using the DEA-bootstrap approach and, in the second, truncated bootstrap regression is applied, in which efficiency scores are regressed on various determining factors.

This paper makes significant theoretical and methodological contributions to the literature. At theoretical level, our study examines efficiency in the sector of credit cooperatives which, unlike the traditional commercial banking sector, has hardly been considered to date. Specifically, this research adds new evidence to the scarce existing literature in Spain in this field. Moreover, our study also contributes by assessing the efficiency in credit cooperatives during the crisis period, since to our knowledge there are hardly any studies for this stage of marked economic and social instability.

Given the hybrid nature of credit cooperatives as Social Economy financial institutions, the paper also adds to current research by constructing for the first time an indicator for measuring the social efficiency of these entities. Both credit cooperative managers and policy makers are showing a growing interest in evaluating the social performance of these singular financial institutions, because information on their financial efficiency alone gives an incomplete view of their global performance (Ory and Lemzeri 2012; Jackson 2015).

Additionally, this study analyses the determining factors of social efficiency in credit cooperatives in an unprecedented way. To our knowledge, there have been very few studies on the determinants of their financial efficiency and none on their social efficiency. Nevertheless, it is key to know the variables that may affect both types of efficiency in these entities in order to improve their global performance and therefore help them survive and thrive in today's environment (Kalmi 2012).

At methodological level, this paper is the first to use a two-stage double bootstrap DEA approach (Simar and Wilson 2007) in this line of research, allowing for more robust and meaningful conclusions than those drawn from the methods that have traditionally been used to evaluate efficiency in the credit cooperatives sector. The conventional DEA model is a linear programming-based non-parametric technique to measure the relative efficiency of a group of homogeneous observations with multiple inputs and multiple outputs. Although this method has several advantages, it also has limitations. In contrast to the previous empirical research using the conventional DEA approach, our study contributes to the existing literature on efficiency in credit cooperatives by applying a two-stage double bootstrap method. While in the first stage of the analysis the limitations of the conventional DEA model to estimate the efficiency scores are corrected for bias using the homogeneous bootstrap procedure (Simar and Wilson 2000), in the second stage bias corrected-efficiency scores are regressed on a set of explanatory variables by employing a truncated regression model with bootstrap (Simar and Wilson 2007), so bias and serial correlation of traditional methodologies – ordinary least square regression and censored Tobit regression – are solved.

The remainder of this paper is organised as follows. Section 2 describes the main features of Spanish credit cooperatives during the period 2008-2014. Section 3 reviews the limited empirical evidence on efficiency in credit cooperatives. The methodology is presented in Section 4, followed by the description of the sample and variables in Section 5. Section 6 presents the results obtained after applying the two-stage double bootstrap DEA methodology, and finally, section 7 concludes.

2 Credit cooperatives in Spain (2008-2014): environment and main features

The financial system in Spain consists of three kinds of banking firms: private banks, saving banks and credit cooperatives. In spite of their relatively limited participation in the overall financial system, Spanish credit cooperatives have been able to increase their market share in assets, credits and deposits between 2008 and 2013. According to the UNACC, in 2013, they held 4.7% of total banking assets as opposed to 4% in 2008, 6.3% of total negotiated credits as opposed to 5.1% in 2008, and 6.8% of total new deposits in Spain as opposed to 5.9% in 2008.

However, in 2014, as part of the financial system restructuring process that has taken place in Spain since the recent crisis, 19 credit cooperatives left the UNACC and were integrated into the Spanish Banks Association (Asociación Española de Banca). This is the reason why the relative market share of credit cooperatives decreased in 2014 compared to 2008 (Fig. 1). Specifically, they held 3.7% of total banking assets, 3.8% of total negotiated credits, and 5.3% of total new deposits in 2014.

Fig. 1 Relative participation of banking firms in the Spanish financial system (2008, 2014) (%)

Unlike some banks and several savings banks, credit cooperatives in Spain have neither declared bankruptcy nor reported losses since the start of the crisis, so no compulsory restructuring process with public sector intervention has been necessary. They have been less affected by the crisis than the rest of Spanish financial entities because they have been less exposed to risk due to their smaller size, have less capacity for leverage in financial markets, and make less use of complex financial engineering instruments (Gutiérrez and Palomo 2012).

Given their small size and new legal requirements to strengthen solvency and decrease risk exposure, Spanish credit cooperatives have carried out a voluntary concentration process, without losing their identity, to try to improve their financial efficiency and competitiveness in times of crisis. Consequently, as shown in Table 1, the number of cooperatives dropped by almost 20% – from 81 to 65– between 2008 and 2013. Surprisingly, in spite of a 5.81% drop in the level of credits in a general context of credit squeeze caused by a global financial crisis, credit cooperatives became stronger during this period, as can be seen by increases in the number of members, volume of new deposits, and total assets of 32.48%, 20.83% and 19.47%, respectively. However, as 19 entities exited the UNACC in 2014, the number of cooperatives diminished by almost 46% between 2008 and 2014 – from 81 to 44, with the resulting decrease in members (-33.67%), employees (-41.44%) and branches (-34.23%). This also led to a fall in assets (-16.61%), loans (-45.83%) and deposits (-9.60%).

Table 1 Basic information on Spanish credit cooperatives (2008-2014)

The main features of Spanish credit cooperatives, which differentiate them from other financial entities, can be summarized as follows: social commitment, territorial nature, traditional retail business model, and democratic corporate governance (Zvolská and Olsson 2012).

First, these entities are characterised by a strong commitment to the Social Economy and local development, so they try to reconcile financial concerns with the cooperative principles of participatory democracy, self-help, self-responsibility, support for the community, and distributive justice (Kalmi 2012). Thus, the very nature of credit cooperatives implies socially responsible behaviour (Server and Capó-Vicedo 2011). In addition, at least 10% of their profits must be assigned every year to the Education and Promotion Fund, which is a special type of fund in these entities for promotion of cooperative values and Corporate Social Responsibility.

Second, the territorial nature of these institutions means that they specialise in their territory of origin, establishing branches close to their customers and thus helping to support employment and growth in that location by financing SMEs, self-employed workers and families. In addition, they work in geographical areas in which other credit entities do not offer services because of their sparse population. According to the UNACC, the percentage of branches in municipalities with less than 25,000 inhabitants to total branches was 64% in 2014. This indicates that credit cooperatives continue to have a preference for their local environment, which helps to achieve financial inclusion for the whole population (Gutiérrez and Palomo 2012).

Third, these entities are also characterised by the development of a traditional retail banking that is closely linked to SMEs, self-employed workers and families (De Castro and Motellón 2011). The very definition of credit cooperatives indicates that their purpose is basically to meet the financial needs of their members. Consistent with the UNACC, more than 91% of their members are individuals, specifically 1,271,034 out of a total membership of 1,384,136 at the end of 2014. The rest of the members linked to legal entities – mostly self-employed workers and SMEs – and to other cooperatives represent 7.73% and 0.44% of total, respectively.

Fourth, regarding their corporate governance, Spanish credit cooperatives are not obliged to maximise value for shareholders but for the cooperative members, and for the community in which they provide their services. In fact, their governance model focuses on individuals and on democratic management by the members (Zvolská and Olsson 2012).

3 Literature review

3.1 Theoretical motivation

3.1.1 Definitions of efficiency

Three main concepts of efficiency are used as a basis for study and practice (Farrell 1957). Firstly, *technical efficiency* implies the use of productive resources in the most technologically efficient manner. In other words, it refers to the maximum possible output from a given set of inputs (*output orientation*) or the minimum quantity of inputs to produce a given quantity of outputs (*input orientation*). Secondly, *allocative efficiency* reflects the ability of an organisation to use these inputs in optimal proportions, given their respective prices and the available production technology. In other words, allocative efficiency is concerned with choosing between the different technically efficient combinations of inputs used to produce the maximum possible outputs. Finally, *cost efficiency* refers to the combination of technical and allocative efficiency, so an organisation will only be cost efficient if it is both technically and allocatively efficient. According to previous literature, this study focuses on technical efficiency (hereinafter referred to as “efficiency”).

3.1.2 Efficiency in the financial sector

During recent decades, sweeping global changes have affected banking institutions worldwide, with financial market deregulation and the resulting intensification of competition, widespread adoption of information technology, and an ongoing process of innovation in financial products and services. Consequently, much attention has naturally focused on the efficiency of banking institutions as a way of better understanding their ability to survive in increasingly competitive environments (Worthington 2010).

Specifically, efficiency in the financial sector can be defined as the degree of optimisation achieved in the use of physical, human and monetary resources for providing different financial services (Worthington 2010; Piot-Lepetit and Nzongang 2014). Thus, it refers to the physical relation between the resources used and service outcomes, including profits, revenue, loans, and financial investments.

3.1.3 Social efficiency in credit cooperatives

Within the financial sector, credit cooperatives work toward a double – financial and social – bottom-line, unlike the conventional financial institutions which work solely toward a financial bottom-line. For this reason, efficiency in credit cooperatives is associated with the physical relation between their financial and social outputs and the resources they use to provide such outputs (Worthington 2010). Since credit cooperatives have borrowed the financial accounting and performance standards of the conventional financial sector, it is more difficult to define and assess their social efficiency than their financial efficiency.

Specifically, the social efficiency concept proposed by Gutiérrez-Nieto et al. (2009) is based on the concept of technical efficiency of Farrell (1957), with the particularity that the former considers a set of social outputs with an output orientation. Accordingly, as the objective is to evaluate the ability of credit cooperatives to provide maximum output for their members and the society as a whole given the resources at their disposal, credit cooperatives are considered socially efficient to the extent that they generate more social outputs without consuming more resources (Ory and Lemzeri 2012).

The selection of input and output variables to measure efficiency in the financial sector needs to be consistent with the production function employed. In this regard, Berger and Humphrey (1997) distinguish between the intermediation approach, in which financial entities are intermediaries between savers and investors, and the production approach, in which they use a set of production factors (inputs) to offer services to their customers (outputs). According to these authors, the approach chosen depends on the context in which the study is made.

We choose the production approach for defining the production function of credit cooperatives because, in addition to being financial institutions whose emphasis is on granting loans, this approach is the only one that allows the social outputs to be considered when estimating efficiency (Gutiérrez-Nieto et al. 2009). Specifically, the achievement of the social aims of Spanish credit cooperatives is measured using two variables: customer socialisation and financial inclusion (Belmonte 2012). On the one hand, since these entities are distinguished from other financial institutions by the weight of member customers over total customers, *customer socialisation* reflects the orientation of their asset operations towards the social mass. On the other hand, *financial inclusion* makes it possible to assess the commitment of credit cooperatives in the fight against the financial exclusion of customers in low-population districts in which commercial banking does not operate.

Moreover, there are three main sources of inputs involved in the activity of these entities: human, physical and monetary. *Human resources* are the main input in any banking activity, especially in credit cooperatives, which use mainly a traditional distribution channel that is labour-intensive and involves direct relations between employees and customers, as opposed to new distribution channels – electronic and telephone banking –. *Physical resources* are another relevant input for the credit cooperative business, which is based on a direct distribution model through a large number of branches. Finally, *monetary resources* refer to the basic activity of any financial entity, including credit cooperatives, that is, to collect deposits to produce loans.

3.2 Empirical evidence

3.2.1 Efficiency measurement in credit cooperatives

Despite the increasing popularity of these peculiar financial entities in many developed countries, there is very little empirical evidence on their efficiency. This gap in the literature stems from their small weight in national financial systems, their limited size and marked territorial dispersion, and the scarce information on them (Server and Capó-Vicedo 2011). Moreover, assessing efficiency in credit cooperatives is more complex than in commercial banks because, in addition to their financial activity, they also play an important social role (Ory and Lemzeri 2012).

To date, the international evidence has only measured the financial efficiency of these entities. Specifically, most of the prior studies have been carried out in Australia (Worthington 1998a, 1999, 2001; Brown et al. 1999; Brown 2006; Garden and Ralston 1999; Ralston et al. 2001; Mcalevey et al. 2010). There is also some interesting research in the United States (Fried et al. 1993, 1999) and Canada (Fortin and Leclerc 2011). In Asia, practically all studies have focused on the financial efficiency of Japanese credit cooperatives (Fukuyama 1996; Fukuyama et al. 1999; Glass et al. 2014). Very little research has been done in this field in Europe and, specifically, mention can be made of the study by Barra et al. (2013) in Italy.

In Spain, the studies by Belmonte and Plaza (2008) and Belmonte (2012) evaluate the total efficiency of Spanish credit cooperatives by considering both the financial and social dimensions of their activity together. Taking the same inputs and financial outputs, but with different specifications for social outputs, the former obtained an average total efficiency of 88.1% from a sample of 82 entities between 1995 and 2007, while the latter showed an average total efficiency of 96.2% from a sample of 78 Spanish credit cooperatives in 2010[1].

[1] The minimum acceptable value for technical efficiency indicators is 50%, while the lowest threshold indicating that an entity is seriously efficient is 90% (Cooper et al. 2007).

Unfortunately, there have been no academic contributions, either international or national, assessing the efficiency of credit cooperatives exclusively from the social perspective[2]. Social efficiency in these banking institutions, therefore, to the best of our knowledge, has not yet been measured.

3.2.2 Determinants of efficiency in credit cooperatives

The empirical research about the efficiency determinants in the credit cooperatives sector is limited. Moreover, the few studies that exist have only tried to identify the factors that explain the financial efficiency of these entities, without providing any empirical evidence on the determinants of their social efficiency (Worthington 1998a, 1998b, 1999, 2001; Fried et al. 1993, 1999; Garden and Ralston 1999; Ralston et al. 2001; Fortin and Leclerc 2011; Glass et al. 2014). Specifically, based on this previous literature, the main explanatory factors of efficiency in credit cooperatives are the following:

Urban concentration: In principle, it can be assumed that as a banking entity increases its degree of urban concentration, its competitors will increase in number and there will be increasing pressure on it to improve its efficiency (Ftiti et al. 2013). From the empirical point of view, Fortin and Leclerc (2011) found that, although credit cooperatives specialise in their local environment, the concentration of their services in towns with greater population density has a statistically significant positive effect on their efficiency. However, it can also be expected that greater concentration of such entities in urban areas will reduce their social efficiency, because it will damage their territorial nature, which is based on helping to achieve financial inclusion for the whole population.

Size: In theory, the largest financial entities tend to be most efficient because they benefit from returns to scale, so the largest ones will have more possibilities for maximising outputs in relation to the optimal production frontier (Wanke and Barros 2014). In line with this, the existing empirical evidence shows that the size of credit cooperatives has a positive and significant effect on their levels of efficiency (Worthington 1998a, 1999; Fried et al 1993, 1999; Fortin and Leclerc 2011; Glass et al. 2014).

Capital adequacy: Theoretically, the financial institutions that capitalise a greater amount of their profit are more efficient because greater capitalisation strengthens them, lowering their financial risk and transmitting greater security to their investors and customers, especially during periods of economic and/or social instability (Mester 1996). Empirically, most of the evidence shows that capital adequacy affects credit cooperatives´ efficiency positively and significantly (Worthington 1998b, Fried et al. 1999; Fortin and Leclerc 2011). However, considering that all banking entities have to comply with a minimum capitalisation rate, if capitalisation goes beyond the real needs for funds, it has been argued that this might damage the relation between the outputs obtained and the inputs used for the purpose (Curi et al. 2012). Only the study by Glass et al. (2014) finds that less capitalised credit cooperatives are more efficient.

[2] Paradoxically, although there is no empirical evidence on the social efficiency of credit cooperatives located in developed countries, there have been many recent studies on this subject for microfinance institutions (MFIs) working in developing countries (Piot-Lepetit and Nzongang 2014; Wijesiri et al. 2015; Mia and Chandran 2015, among others). Microfinance institutions are credit entities that also have an important social role, mainly in poorly-developed countries where they give loans to social groups that are excluded from the traditional financial system. It is precisely the loans policy of such entities that prevents the existing evidence on their social efficiency from being transferred to credit cooperatives.

Number of service points: This variable controls for the quality of the organisational structure of financial institutions to the extent that, in general, the number of branches can be considered to have a negative effect on the skill of the head office in promoting efficient behaviour. However, there is also another argument that is especially valid from the social perspective which is that service points are another of the outputs offered by financial entities, resulting in a positive effect for their efficiency (Mester 1996). The existing empirical studies only find a negative and significant relation between this variable and the efficiency of credit cooperatives (Worthington 1998b; Fortin and Leclerc 2011).

Regional effect: The heterogeneity existing among the different regions of a country, especially in terms of regulation and macroeconomic conditions, might also help explain the differences in efficiency of their credit cooperatives. Several empirical studies have shown that there is a regional effect, which suggests that the efficiency of these entities varies depending on their geographical location within a specific country (Worthington 1998b, 1999; Fried et al. 1993; Glass et al. 2014).

4 Research methodology

We apply a two-stage double bootstrap Data Envelopment Analysis (DEA) approach. In the first stage, efficiency scores are estimated using a conventional DEA model based on a set of input and output variables and then, in the second stage, DEA efficiency estimates are regressed on some explanatory variables by applying a truncated regression model. Specifically, we use the Algorithm 2 developed by Simar and Wilson (2007), which incorporates the bootstrap technique in both conventional DEA and truncated regression models. This procedure is performed using *FEAR* software package (Wilson 2008).

4.1 Outlier detection

The non-parametric efficiency estimators are highly sensitive to the presence of outliers or atypical observations, which are considered particularly troublesome for DEA (Bogetoft and Otto 2011). Therefore, before measuring efficiency, it is important to detect outliers and to treat them appropriately, since they can increase noise and distort the results.

Different procedures exist to deal with outliers in non-parametric models. In our study, the method developed by Wilson (1993, 2010) is adopted since it does not a priori require any specific direction for the model and it allows a group of outliers to be identified at the same time. Particularly, Wilson considers a set *S* of *n* observations *S*= (1,... , n); where $L \subset S$ contains *i* elements and $i < n$; and $\mathrm{R}^{(\mathrm{i})}_{\mathrm{min}}$ denotes the observed minimum value of $\mathrm{R}^{(\mathrm{i})}_{\mathrm{L}}$ for all $\binom{\mathrm{n}}{\mathrm{i}}$ possible subsets *L* of size *i* observations[3]. To identify outliers more easily, it is advisable to carry out a graphical analysis in which the ordered pairs

[3] See Wilson (1993, 2010) for details.

$(\mathrm{i}, \log[\mathrm{R}_{\mathrm{L}}^{(\mathrm{i})}/\mathrm{R}_{\min}^{(\mathrm{i})}])$ are plotted, where *i* is the number of deleted observations and the ratio is computed for each of the possible subsets *L* of size *i*. The choice of stopping point in the analysis *i* is arbitrary but higher values of *i* become computationally intractable. An examination of the separation between the smallest log ratios indicates possible outliers. Wilson also points out that some outliers can be masked by others. To avoid this masking effect, the analysis has to be repeated without those units. Finally, once identified, all outliers must be eliminated from the sample.

4.2 First stage: estimation of DEA efficiency scores

The goal of the first stage of the analysis is estimation of DEA efficiency scores. Ratio indicators and parametric and non-parametric frontier methods are the most common approaches for measuring the efficiency of organisations (Lampe and Hilgers 2015). On the one hand, ratios are a traditional method for monitoring organisational performance. However, estimating efficiency based on the notion of these ratios will be distorted unless they have been properly adjusted. Despite the undeniable greater accuracy of adjusted data, estimates on adjustments are not always easy to make and data are seldom available. Moreover, ratios in isolation provide little help when considering the effects of economies of scale, estimating overall performance of firms and identifying benchmarking policies (Wijesiri et al. 2015).

On the other hand, frontier methods are a more sophisticated and powerful way of benchmarking firms. The frontier approach relates to the economic notion of production frontier which, in this study, represents maximum outputs generated by a production unit given the level of its inputs, and allows the estimation of overall performance measures and identification of the best-performers (Piot-Lepetit and Nzongang 2014). Specifically, Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) are the most common frontier techniques for measuring efficiency[4] (Wijesiri et al. 2015). SFA is a parametric frontier method, that is, it evaluates efficiency by estimating a multivariate statistical model to discover explanatory variables that differ across organisations and it requires a prior specification of the functional form of the production function. In contrast, DEA is a non-parametric frontier method that aims to measure efficiency by estimating the optimal level of outputs depending on the level and mix of inputs, and it does not need the previous definition of a specific function form.

There are several advantages of DEA over SFA, which justify researchers' preference for it (Bogetoft and Otto 2011). First, DEA can capture multiple outputs and inputs at the same time to assess efficiency. Second, it avoids the need to make assumptions regarding the functional form of the best-practice frontier. Third, non-frontier units are directly compared against the best practice or the peer combination of units, which may be of great value for practitioners and public authorities. Fourth, it does not require the assumption of fulfilment of statistical hypotheses such as normality or heteroscedasticity. Finally, it is a method thought to work well with less data and limited sample sizes. For these reasons, the DEA method is the most widely-accepted estimator for analysing the efficiency of organisations in

[4] See Greene (1993), Berger and Mester (1997) and Coelli et al. (1998) for details on both frontier methods.

several industries, which use the same multiple inputs and produce the same multiple outputs (Lampe and Hilgers 2015). Consequently, we also employ the DEA method in our analysis.

The conventional DEA model is a non-parametric method based on linear programming that calculates the efficiency score of a given organization (Decision Making Unit, DMU) in comparison with the performance of other homogeneous organizations by constructing an efficient frontier where the best practices are situated. Thus, each DMU is assigned an efficiency indicator between 0 and 1, with higher scores indicating more efficient organization relative to other organizations in the sample. So, a score of 1 indicates that a DMU lies on the efficient frontier and hence can be considered a fully efficient unit, while relative inefficiency is measured by the radial distance between the DMU and the frontier. Specifically, given the output orientation of this study, efficiency measures provide the amount of outputs to be increased without changing the current level of inputs.

DEA can be implemented by assuming either constant returns to scale (CRS) or variable returns to scale (VRS)[5]. Following numerous studies on the efficiency of credit cooperatives (Fried et al. 1993, 1999; Ralston et al. 2001; Worthington 2001; Brown 2006; Barra et al. 2013), we employ the DEA model under the variable returns to scale (VRS) assumption because it is more consistent with the environment of imperfect competition in which credit cooperatives operate.

According to the VRS output-oriented DEA model, efficiency indicators can be obtained by solving the following linear programming problem (Eq. 1), which must be resolved *n* times, one for each DMU in the sample:

$$\hat{\delta}_i = max_{\hat{\delta}_i\lambda}\left\{\delta > 0 \middle| \hat{\delta}_i y_i \leq \sum_{i=1}^{n} y_i\lambda; x_i \geq \sum_{i=1}^{n} x_i\,\lambda; \sum_{i=1}^{n}\lambda_i = 1; \lambda \geq 0\right\}; \text{ i=1, .., n DMUs} \quad \textbf{[1]}$$

where y_i is a vector of outputs; x_i is a vector of inputs; λ is an *n* x 1 vector of constants which measures the weights used to compute the location of an inefficient DMU aiming to become efficient; and $\hat{\delta}_i$ is the efficiency score for the *i*th DMU under the VRS assumption. If $\hat{\delta}_i = 1$, the *i*th DMU is fully efficient, and if $\hat{\delta}_i < 1$, the *i*th DMU is relatively inefficient.

Although the conventional DEA model presents advantages, it still suffers from some limitations. In addition to the high sensitivity of its results to the presence of outliers discussed in the previous section, the DEA method does not allow for statistical inference and consequently its results are biased because it ignores sampling and measurement errors. To mitigate this drawback, we take the route initiated by Simar and Wilson (2000) to adopt the homogeneous bootstrap algorithm in the first stage of the analysis, which combines the conventional DEA model with the bootstrap technique to infer the statistical properties of

[5] The "*constant returns to scale (CRS) DEA model*" was proposed by Charnes et al. (1978) and is only appropriate when all organizations operate at an optimal scale, which is difficult because of the existence of imperfect competition, government regulations, constraints on finance, etc. For this reason, Banker et al. (1984) proposed the "*variable returns to scale (VRS) DEA model*".

efficiency scores. As a result, a set of bias-corrected efficiency scores is generated (denoted by $\hat{\hat{\delta}}_i$). But Efron and Tibshirani (1993) indicate that bias correction may introduce additional noise. For this reason, Simar and Wilson (2000) advise that bias-corrected efficiency scores should only be used when the following ratio r_i is well above unity (Eq. 2),

$$r_i = \frac{1}{3}\left(\widehat{bias}_B^2\left[\hat{\delta}(x,y)\right]/\hat{\sigma}^2\right) \qquad \textbf{[2]}$$

where r_i is a statistical test value, which allows us to assess whether the bias correction might increase mean square error; $\hat{\sigma}^2$ is the variance of the bootstrap values; *B* is the number of replications and $\hat{\delta}$ is the original efficiency estimate. This issue is also considered in our empirical study, so the resulting useful efficiency scores are denoted by $\tilde{\delta}$.

4.3 Second stage: estimation of the truncated regression model

The goal of the second stage of the analysis is to examine the impact of a set of hypothesized explanatory variables on the useful efficiency scores obtained in the previous stage. To accomplish this goal, we employ the bootstrap truncated regression model included in the second stage of the Algorithm 2 developed by Simar and Wilson (2007), which assumes that the explanatory variables only affect the production process through the probability of being more or less efficient, but not the efficient frontier.

The traditional methodologies in the second stage of analysis – ordinary least square and censored Tobit regressions – have been widely criticized because explanatory variables are correlated with the error term, and input and output variables are correlated with explanatory variables. Moreover, DEA efficiency estimates used in the second stage are serially correlated and hence yield inconsistent and biased estimates (Wijesiri et al. 2015). As a result, standard methods for inference in the second-stage regression are invalid.

Simar and Wilson (2007) address this issue by proposing an alternative double bootstrapped procedure (Algorithm 2) that permits valid inference while simultaneously generating standard errors and confidence intervals for the efficiency estimates. Specifically, as DEA scores are bounded within the interval [0, 1], a bootstrap truncated regression model is used in the second stage which has been demonstrated to provide consistent and non-biased estimates (Simar and Wilson 2011). For this reason, our study also applies a bootstrap truncated regression, where the useful efficiency scores $\tilde{\delta}_i$ yielded in the first stage of the analysis are regressed on a set of explanatory variables using the following regression model (Eq. 3):

$$\tilde{\delta}_i = \alpha + \beta z_i + \varepsilon_i, \quad i = 1, \dots, n \qquad \textbf{[3]}$$

where α is a constant term; β is a vector of parameters to be estimated; z_i is a vector of specific explanatory variables that are expected to affect the efficiency of the *i*th DMU; and ε_i is an error term assumed to be $N(0, \sigma_\varepsilon^2)$ distributed with right truncation at $(1 - \alpha - \beta z_i)$.

5 Sample and variables

5.1 Population and initial sample

The target population for this study comprises all the Spanish credit cooperatives belonging to the UNACC between 2008, when the latest financial crisis began, and 2014, the last year for which information is available. However, as a result of the financial system restructuring process that has taken place in Spain during this period, the number of active credit cooperatives varies in each of the seven years analysed. Specifically, after including new entities created and filtering out those that disappeared in each year from 2008 to 2014, the sum of all active entities is 81 in 2008, 80 in 2009, 78 in 2010, 74 in 2011, 68 in 2012, 65 in 2013 and 44 in 2014. The initial sample is therefore an unbalanced data panel including a total of 490 DMUs or observations, which coincides with the population size.

5.2 Outlier detection and final sample

The results obtained after applying the outlier detection procedure developed by Wilson (1993, 2010) are presented in Fig. 2. In particular, it displays the graphical analysis of the ordered pairs $(\mathrm{i}, \log[\mathrm{R}_\mathrm{L}^{(\mathrm{i})}/\mathrm{R}_{\mathrm{min}}^{(\mathrm{i})}])$ and shows the lowest values of the log-ratios. The stopping point arbitrarily chosen for our analysis is *i* = 12.

Fig. 2 Outliers detection

We search the points in this graph where there is a gap between the points above 0 and the point at 0 for each observation *i*. A dashed line connects the second lowest values for each *i* to illustrate the separation among the smallest ratios. According to Fig. 2, a total of 11 outliers are initially identified. To avoid the masking effect, we repeat the process without them. As a result, we decide to remove seven additional outliers. Consequently, after eliminating 18 atypical observations from the initial sample, the final sample includes 472 DMUs or observations.

5.3 Variables

5.3.1 Input and output variables

Under the production approach, this paper takes as its point of reference the specification and measurement of inputs and social outputs used by Belmonte (2012) for evaluating the total efficiency of credit cooperatives in Spain. Specifically, the input variables are personnel expenses, amortisation expenses, and interest expenses, while the social output variables are customer socialisation and financial inclusion. So, our study meets the basic requirement for the efficiency estimates to be robust and reliable (Cooper et al. 2007): the number of DMUs must be at least the maximum between $m*s$ or $3(m+s)$, with m and s being the number of input and output variables, respectively. We explain below how these variables are measured from the Statistical Yearbook of Credit Cooperatives published by the UNACC (www.unacc.com). Data expressed in monetary units are deflated – at constant prices for 2008 – using the GDP deflator, in order to avoid inflation-related distortion of the results.

Input variables:

- *Personnel Expenses* (PERS)*:* This variable refers to the annual cost of the human resources used by credit cooperatives for performing their activity (in thousands of euros).
- *Amortisation Expenses* (AMOR): This covers the annual cost of the physical capital consumption associated with the activity carried out by credit cooperatives (in thousands of euros).
- *Interest Expenses* (INTE): This is an indicator of the cost of the financial resources captured at retail level; that is, the annual cost of deposits (in thousands of euros).

Social output variables:

- *Customer Socialization* (CSOC): This variable is defined as the ratio between loans to customers and the total number of members (in thousands of euros per member).
- *Financial Inclusion* (FINC): This is measured by the ratio between the number of branches in municipalities having less than 25,000 inhabitants and total branches (in %).

5.3.2 Determinant variables

Based on the previous literature, five explanatory variables are used for examining the determinants of efficiency in the credit cooperatives sector. They are built from the Statistical Yearbook of Credit Cooperatives available on the website of the UNACC (www.unacc.com):

- *Urban Concentration* (URB): This variable is made operational by a dummy that takes the value of 1 when the proportion of branches in municipalities with more than 25,000 inhabitants over the total is greater than the annual average for all the credit cooperatives analysed, and 0 otherwise (Fortin and Leclerc 2011).

- *Size* (SIZ): This is measured by total assets of credit cooperatives (in thousands of euros, with logarithmic transformation for the statistical analysis) (Worthington 1998a, 1999, 2001; Fried et al. 1993; 1999; Ralston et al. 2001; Fortin and Leclerc 2011; Glass et al. 2014).

- *Capital Adequacy* (CAP): This variable captures the proportion of equity to total assets (in %), so that, the higher the ratio, the lower the financial leverage and therefore the lower the financial risk of credit cooperatives (Worthington 1998a, 1998b, 1999, 2001; Fried et al. 1993, 1999; Fortin and Leclerc 2011; Glass et al. 2014).

- *Number of Service Points* (SER): This is measured by the total number of branches that credit cooperatives have, with logarithmic transformation for the statistical analysis (Worthington 1998b; Fried et al. 1999; Ralston et al. 2001; Fortin and Leclerc 2011).

- *Regional Effect* (REG): Since the credit cooperatives analysed are located in 15 Spanish regions (Andalusia, Aragon, Asturias, Castile-La Mancha, Castile and Leon, Catalonia, Valencian Community, Extremadura, Galicia, Balearic Islands, Canary Islands, Madrid, Murcia, Navarre and Basque Country), this study takes into account their location within Spain by including 14 regional dummy variables.

From these explanatory variables, the following specification of the truncated regression model is estimated in order to study the determinants of social efficiency (Eq. 4):

$$\tilde{\delta}_i = \alpha + \beta_1 \mathrm{URB}_{i,t} + \beta_2 \ln(SIZ)_{i,t} + \beta_3 CAP_{i,t} + \beta_4 \ln(SER)_{i,t} + \beta_5 REG_{i,n} + \varepsilon_i \qquad \textbf{[4]}$$

where the dependent variable $\tilde{\delta}_i$ refers to the useful efficiency score from the first stage of the *i*th DMU; α is a constant term; $\beta_1, \beta_2, \ldots \beta_5$ are the parameters to be estimated; $\mathrm{URB}_{i,t}$ is the urban concentration of the *i*th DMU in period *t*; $\mathrm{SIZ}_{i,t}$ is the size of the *i*th DMU in period *t*; $\mathrm{CAP}_{i,t}$ is the capital adequacy of the *i*th DMU in period *t*; $\mathrm{SER}_{i,t}$ is the number of service points of the *i*th DMU in period *t*; $\mathrm{REG}_{i,t}$ is the regional location of the *i*th DMU in period *t*; and ε_i is an error term.

6 Results

The main descriptive statistics for both input and output variables and the variables used to measure the efficiency determinants appear in Table 2.

Table 2 Descriptive statistics

Table 3 presents the Pearson correlation coefficients between the efficiency determinants when these are measured using a continuous variable. Specifically, it shows that there is a high positive and statistically significant correlation ($r = 0.929$; $p > 0.01$) between size (SIZ) and the number of service points (SER). Study of the variance inflation factors (VIF) reveals that, with the exception of these two variables (VIF(SIZ) = 14.23; VIF(SER) = 13.43), the other VIFs are below 10 (Kleinbaum et al. 1998). Thus, to avoid problems of multicollinearity, these two variables are introduced in separate regressions, together with the other explanatory factors, in the second-stage truncated regression analysis.

Table 3 Correlation coefficients between the efficiency determinants

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6.1 First stage: social efficiency scores

The bootstrap DEA approach is applied by using 2,000 repetitions with a confidence level of 95%, so that in order to build a single efficient frontier, each credit cooperative is treated as a separate, different observation in each year of the study period (Moradi-Motlagh et al. 2015).

Table 4 shows mean, standard deviation, minimum, and maximum values for the original, bias-corrected and useful estimates of social efficiency in Spanish credit cooperatives during the period 2008-2014. It also shows both the number and the percentage of fully efficient DMUs in each case. As the useful efficiency values $(\tilde{\delta})$ are the closest to the real efficiency, they are the ones that are considered for interpreting the results[6].

Table 4 Social efficiency estimates (2008-2014)

On the one hand, the mean score for the social efficiency of credit cooperatives in Spain reaches an acceptable value of 66.42% – well above 50%, which is the minimum tolerable value for estimates of technical efficiency. Thus, in order to be fully efficient $(\widetilde{\delta} = 1)$, these entities should have increased their social outputs by 33.58% given the resources at their disposal. Since to our knowledge there is no empirical background on the social efficiency of credit cooperatives, no comparison can be made with the existing evidence.

On the other hand, 35.38% of the DMUs analysed (167 observations) are fully efficient from the social point of view ($\tilde{\delta} = 1$). Fig. 3 represents the position taken by the 472 total DMUs regarding the estimates for social efficiency during the period 2008-2014. Specifically, it depicts the number of DMUs sorted from a lower to a higher useful efficiency score. As both graphs show, social efficiency reaches values above 50% $(\tilde{\delta} > 0.5)$ for 72.25% of all DMUs (341 observations), and values below 50% $(\tilde{\delta} < 0.5)$ for the remaining 27.75% (131 observations).

Fig. 3 Number of DMUs sorted by useful social efficiency scores

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6.2 Second stage: determinants of social efficiency

[6] The conventional DEA model, which is applied in all prior studies on efficiency in credit cooperatives, gives the values for original efficiency without taking into account any sample noise in the estimates, so the results may be misleading.

Table 5 presents the results from the two alternative specifications of our bootstrap truncated regression model, where useful social efficiency scores for Spanish credit cooperatives over the period 2008-2014 are regressed on a set of explanatory variables. Both regressions are estimated by using 2,000 repetitions with a confidence level of 95%.

Table 5 Determinants of social efficiency

The findings show that the urban concentration (URB) of these financial institutions seems to have a statistically significant impact on their social efficiency. More specifically, the coefficients obtained suggest that entities with a greater proportion of branches in urban areas are socially less efficient. Moreover, this variable is associated with the highest effect size.

Regarding the rest of the specific characteristics of credit cooperatives examined in this research, both the size (SIZ) and the number of service points (SER) of the entity also seem to be statistically significant determinants of their social efficiency. In particular, the larger the credit cooperative, the greater its capacity for obtaining a higher level of social outputs from the resources at its disposal. Moreover, institutions with a larger number of branches are socially more efficient, managing their social activity better than those with less service points. In contrast, the capital adequacy ratio (CAP) does not have a significant impact on the social efficiency of credit cooperatives.

The results obtained also suggest the importance of the regional effect (REG) for the social efficiency of Spanish credit cooperatives so that those situated in Madrid and the Basque Country are socially more efficient while those in Andalusia, Aragon and Catalonia are less efficient.

Finally, since as far as we know, there have been no studies on the determinants of the social efficiency of credit cooperatives, our findings show that at least in Spain the internal variables that have traditionally been considered for explaining the financial efficiency of these entities are also suitable for determining their social efficiency.

7 Concluding remarks

7.1 Conclusions

This paper examines social efficiency and its determinants in Spanish credit cooperatives during the period 2008-2014. After applying an innovative two-stage double bootstrap DEA approach, its main conclusions are the following.

Results from the *first stage* show that Spanish credit cooperatives achieved a relative level of social efficiency of 66.4% between 2008 and 2014, while the minimum tolerable value is 50%. That is, they generated 33.6% less than the maximum level of social outputs that might be expected if they had used their human, physical, and financial inputs better. Consequently, the social performance of Spanish credit cooperatives has been quite acceptable, so it is possible to conclude that they managed their social activity reasonably well during the recent economic and financial crisis. Thus, this period of strong economic and social instability seems not to have significantly affected the social outputs of Spanish credit cooperatives, possibly because their main mission is not to maximise profits, as in the traditional commercial banking sector, but to achieve a social purpose, primarily that of meeting the financial needs of their members and of the geographical areas in which other financial entities do not provide services because of their sparse population.

Regarding the *second stage*, our findings suggest that Spanish credit cooperatives have certain characteristics that may affect the relation between the inputs and the social outputs of their production process, significantly affecting their levels of efficiency. More specifically, the entities that have a larger proportion of branches in urban areas are less efficient at a social level. This result is completely in line with expectations in that credit cooperatives are clearly distinguished from other banking intermediaries by their territorial nature, which mitigates the risk for the small municipalities in which they operate of being excluded from financial activity. As a result, when Spanish credit cooperatives concentrate their branches in urban areas, their social efficiency is reduced because this favours the financial exclusion of areas with low population density.

Moreover, there are two internal characteristics of these financial institutions – size and number of service points – that have a relevant favourable effect on their level of social efficiency, thus benefiting both their members and the various stakeholders in the territory in which they are located. It can therefore be assumed that the larger the entities, the more likely they are to be subject to increasing returns to scale so their capacity to optimise the social outputs obtained from their inputs will be greater. Also, the greater the number of branches, the greater the social efficiency of credit cooperatives, because of their network of services will be larger both for their members and for the families and firms in the small towns where they tend to be situated.

Finally, social efficiency also varies significantly depending on the regional location of credit cooperatives in Spain. Specifically, the regulatory and institutional framework of Madrid and the Basque Country might enable their entities to be more efficient socially; while the concentration processes in the sector aiming to boost financial efficiency – which have mostly taken place in Andalusia, Aragon and Catalonia – might explain why credit cooperatives located in these regions are socially less efficient.

7.2 Managerial and governance implications

Credit cooperatives must be both financially and socially efficient to improve their competitiveness in the new international context so that they can continue performing their important financial and social activity (Kalmi 2012). Our findings indicate that Spanish credit cooperatives had relative social inefficiency of 33.6% during the period 2008-2014, which cannot be ignored if they want to improve their social and global performance in the near future. This study considers the various factors affecting social efficiency, so it contributes to a deeper awareness of potential directions for future action in credit cooperatives to achieve more successful social management.

Firstly, unlike commercial banks, which do not reach small towns because of the high cost to income ratio, Spanish credit cooperatives have traditionally aimed to achieve proximity with their customers by establishing branches in small towns. However, over recent years, there has been a clear trend towards the opening of branches in urban areas, raising doubts about the social vocation of such entities. Our results indicate that this interest in large urban areas substantially worsens the social efficiency of credit cooperatives. In consequence, if these entities wish to increase their social performance, they should focus, once again, on the local environment.

Secondly, credit cooperative managers should promote merger and acquisition processes or establish strategic alliances among these entities as a means of growing both their size and the number of branches, increasing their social efficiency while coping with the process of economic globalisation and the requirements of the market and the European Union. Such strategies would enable credit cooperatives to access complementary resources and capabilities to meet better the present and future needs of their members, customers and the society in general.

Regarding the governance implications of this paper, it would be advisable for the Spanish policy makers to try to consolidate the original social function of credit cooperatives as they are key for the economic development and financial integration of the territories where they work. Theoretically, credit cooperatives are a type of socially responsible banking that is necessary for the country's economic and social development because they help finance the real economy and return part of their profits to society. Our empirical findings suggest that in fact most credit cooperatives in Spain have been quite efficient from a social perspective in the crisis period. Nevertheless, the restructuring process of the Spanish financial system that has taken place during the crisis – whereby some credit cooperatives have evolved into specific, universal banks and the remainder are now treated as banking firms that are in competition with commercial banks – could lead them to disappear, damaging both their members and their customers and negatively affecting the economic recovery process in Spain.

Moreover, regional and local governments in Spain, especially in areas where the less socially efficient entities are located, could adopt institutional and regulatory measures to improve the social efficiency of credit cooperatives in their respective territories, and could allocate public funds to them based on a criterion of good social management.

7.3 Limitations and future research

The main limitation of this study lies in the selection and measurement of the input and output variables. Choosing such variables is complex because of the limited data available in Spain, the difficulties of quantifying intangible social outputs, and the lack of indicators measuring qualitative aspects of the social activity of such entities. So, for future research, more and better input and output variables should be studied, wherever possible, so that estimates of the social efficiency of these entities reflects their social production process better. Moreover, research into changes in the social productivity of Spanish credit cooperatives during the crisis period as a result of variations in efficiency and/or technological change could be a logical extension to this paper. Finally, it would be interesting to analyse whether social and financial efficiency are complementary or mutually exclusive in these singular financial entities.

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Table 1 Basic information on Spanish credit cooperatives (2008-2014)

	Credit cooperatives	Members	Employees	Branches	Assets (million €)	Loans (million €)	Deposits (million €)
2008	81	2,086,896	20,940	5,141	113,010	94,902	75,864
2009	80	2,223,603	20,722	5,079	119,455	97,757	80,637
2010	78	2,320,634	20,352	5,051	121,580	98,359	93,706
2011	74	2,438,052	20,036	4,928	126,891	96,691	90,071
2012	68	2,554,627	19,674	4,832	131,649	93,548	88,231
2013	65	2,764,746	18,910	4,651	135,019	89,389	91,665
% 2008-2013	**-19.75%**	**32.48%**	**-9.69%**	**-9.53%**	**19.47%**	**-5.81%**	**20.83%**
2014	44	1,384,136	12,263	3,381	94,235	51,405	68,579
% 2008-2014	**-45.68%**	**-33.67%**	**-41.44%**	**-34.23%**	**-16.61%**	**-45.83%**	**-9.60%**

Source: Authors´ own elaboration based on data from the UNACC (2008, 2014)

Table 2 Descriptive statistics

n = 472 DMUs	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
Input variables				
PERS	8,490.71	13,357.35	139	85,204
AMOR	1,063.01	1,884.63	2.96	12,176.47
INTE	18,073.89	34,154.72	107.46	324,269
Outputs variables				
CSOC	73.05	287.46	4.66	2,651.85
FINC	64.41	37.69	0	100
Efficiency determinants				
URB	0.62	0.48	0	1
SIZ	1,045,895.69	1,761,860.47	8,046	9,593,067
CAP	9.38	4.19	1.12	73.66
SER	50.58	84.69	1	518

PERS: Personnel Expenses (in thousands euros); AMOR: Amortisation Expenses (in thousands euros); INTE: Interest Expenses (in thousands euros); CSOC: Customer Socialization (in thousands euros / member); FINC: Financial Inclusion (in %); URB: Urban Concentration (dummy: 1/0); SIZ: Size (in thousands euros); CAP: Capital Adequacy (in %); SER: Number of Service Points (in units)

Table 3 Correlation coefficients between the efficiency determinants

n = 472 DMUs	SIZ	CAP	SER
SIZ	1		
CAP	-0.239	1	
SER	0.929***	-0.243	1

SIZ: Size (in thousands euros); CAP: Capital Adequacy (in %); SER: Number of Service Points (in units)

*** Significant at the 1% level (2-tailed)

Table 4 Social efficiency estimates (2008-2014)

n = 472 DMUs	**Original efficiency** **($\widehat{\delta}$)**	**Corrected efficiency** **($\widehat{\widehat{\delta}}$)**	**Useful efficiency** **($\widetilde{\delta}$)**
Mean	0.6649	0.6555	0.6642
Standard Deviation	0.3693	0.3635	0.3690
Minimum	0.0035	0.0035	0.0035
Maximum	1	0.9988	1
Fully efficient DMUs	172	0	167
Fully efficient DMUs (%)	36.44%	0.00%	35.38%

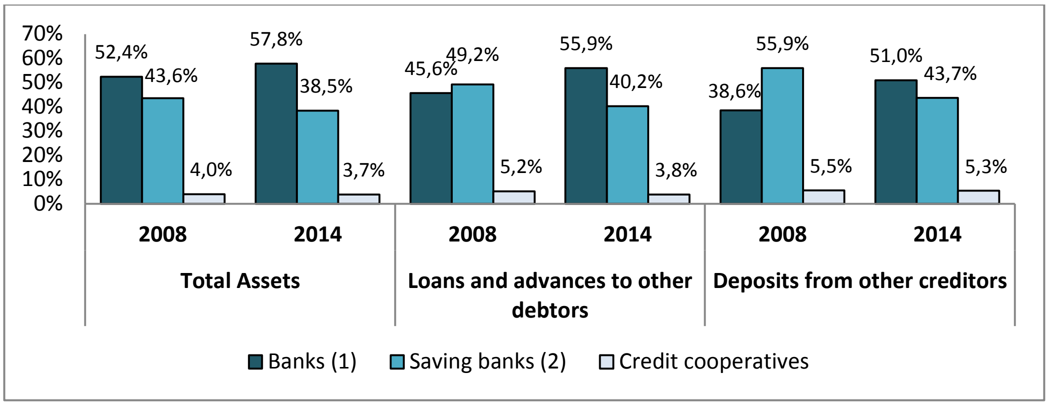
Table 5 Determinants of social efficiency

Variable	*ß* **coefficients** (Bootstrap Standard Errors)	
Constant (α)	-1.4958*** (0.1701)	-0.0831 (0.0655)
URB	-0.5009*** (0.0478)	-0.4331*** (0.0552)
SIZ	0.1328*** (0.0144)	
CAP	0.0022 (0.0062)	0.0023 (0.0059)
SER		0.1184*** (0.0141)
REG (Regional dummies)	Yes	Yes
Sigma	0.1879*** (0.0129)	0.1743*** (0.0129)
Number of observations	305	305
Log likelihood	138.4370	153.4146
Wald $\chi^2(17)$	3944.16***	11326.51***

URB: Urban Concentration (dummy: 1/0); SIZ: Size (in thousands euros); CAP: Capital Adequacy (in %); SER: Number of Service Points (in units); REG: 14 regional dummies to control for the regional location within Spain

*** Significant at the 1% level

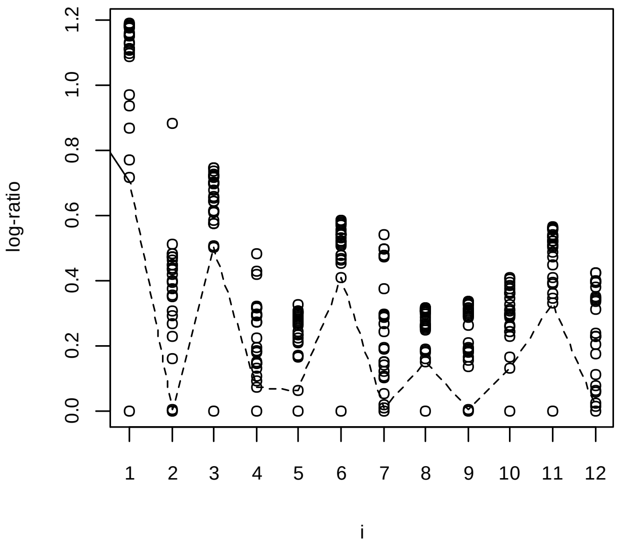
Fig. 1 Relative participation of banking firms in the Spanish financial system (2008, 2014) (%)



Source: Authors´ own elaboration based on data from the UNACC (2008, 2014), Asociación Española de Banca (2008, 2014) and Confederación Española de Cajas de Ahorros (2008, 2014). All data come from individual financial statements

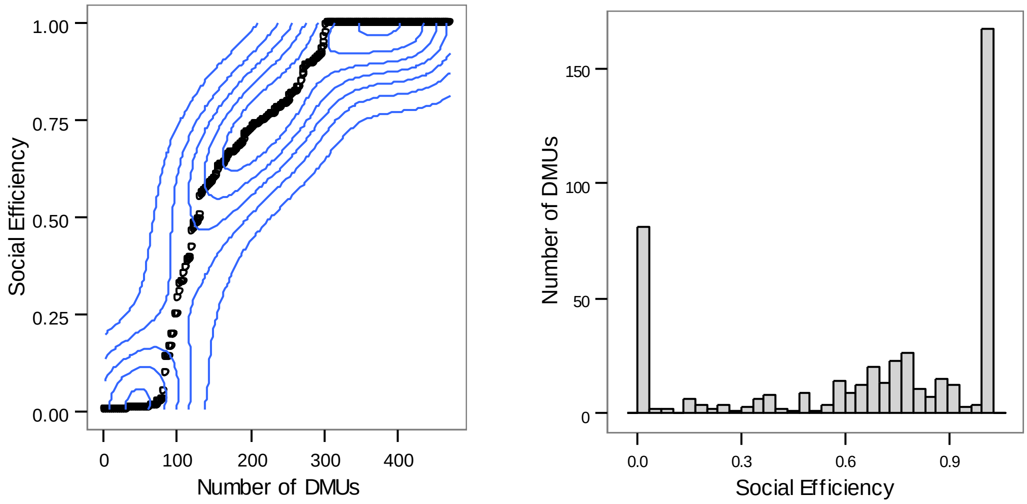
(1) Both Spanish banks and branches of foreign entities operating in Spain
(2) Only entities belonging to the Confederación Española de Cajas de Ahorros with direct financial activity at the end of 2014: Caixabank, S.A; Bankia, S.A; Catalunya Bank, S.A; Abanca Corporación Bancaria, S.A.; Kutxabank, S.A; BMN,S.A.; Unicaja Banco, S.A.; Ibercaja Banco, S.A.; Liberbank, S.A.; Caja de Ahorros y Monte de Piedad de Ontiyent and Caixa d'Estalvis de Pollença-Colonya

Fig. 2 Outliers detection



Source: Authors´ own elaboration.

Fig. 3 Number of DMUs sorted by useful social efficiency scores



Source: Authors´ own elaboration