Agricultural Finance Review

Emerald Article: Why do credit cooperatives disappear?: The determinants of Portuguese agricultural credit co-operatives failure

Paula Cabo, João Rebelo

Why do credit cooperatives disappear?

The determinants of Portuguese agricultural credit co-operatives failure

Paula Cabo
Department of Social Sciences, School of Agriculture, Polytechnic Institute of Bragança, Bragança, Portugal, and
João Rebelo
Department of Economics, Sociology and Management, University of Trás-os-Montes and Alto Douro, Vila Real, Portugal

Abstract

Purpose – The paper aims to identify "problematic" agricultural credit co-operatives (CCAM) and to evaluate their risk of insolvency as a function of financial indicators, providing regulators and other stakeholders with a set of tools that would be predictive of future insolvency and perhaps bankruptcy.

Design/methodology/approach – Using a database of CCAM failures in the period between 1995 and 2009, statistical models of failure of CCAM, are estimated and compared, using logistic regression analysis and multiple discriminant analysis for assessing the potential failure of CCAM as a function of financial/economical indicators.

Findings – The paper identified the variables customer resources growth, transformation ratio, credit overdue, expenses ratio, structural costs, liquidity, indebtedness and financial margin as determinants of CCAM failure. It suggests that CCAM take measures geared to boosting business, to shoring up the financial margin and the deposit base, to bolstering the complementary margin and to improving the credit recovery processes. Additionally it is necessary to increase cost efficiency, rationalizing structures and procedures consistent with reducing operating costs without detriment to the quality of service provided.

Originality/value – This paper helps to understand why agricultural credit co-operatives fail.

Keywords Insolvency, Agricultural credit co-operatives, Logit analysis, Multiple discriminant analysis, Agriculture, Credit, Portugal

Paper type Research paper

1. Introduction

The 2008 financial crisis, and the European sovereign crisis that follow it, left no doubt that if big banks get into troubles taxpayers end up bailing out them, showing that banks which are global and private in life are national and public in death. This is one reason because the robustness of the European banking system is a current concern and a policy priority to national authorities.

The financial crisis and subsequent economic recession also highlight both the strengths and weaknesses of co-operative banks (*The Economist*, 23 January 2010). In the Portuguese case, there is no doubt that the improvement of co-operative banking performance is a strategic and operational necessity to ensure the economic and financial survival of Agricultural Credit Co-operatives, Caixas de Credito Agricola Mutuo (CCAM). In a country struggling with the depopulation of its rural regions, CCAM robustness

Agricultural Finance Review
Vol. 72 No. 3, 2012
pp. 341-361

0002-1466
DOI 10.1108/00021461211277222

is a fundamental matter for all agro-business players and stakeholders. The co-operative nature and unique business approach make the CCAM a powerful force for Portuguese economic recovery, working as a stabilizing factor in the banking industry and a booster of local development, particularly in regions which economy is supported by agriculture.

Although Credito Agricola performance, as a group, compares favourably with that of other credit institutions, individual CCAM occasionally do enter in distress, as illustrated by past events. The increasingly large size of the CCAM raises concerns regarding the resolution of potential distress situations, given some of the rules governing co-operatives.

In the past, resolution of CCAM drawbacks typically involved the merger or incorporation of the weak CCAM with another CCAM (Cabo and Rebelo, 2005). However, this strategy is more difficult to apply to a large systemic CCAM and CCAM regional orientation can be a constraint to find an adequate merger partner, without losing the individual territorial identity.

As a system, in the process of strategic planning, more specifically, in the phase of diagnosis and subsequent adoption of plausible prescriptions by the main stakeholders (members, customers, staff and others partners working for the group, local communities, suppliers and the state (as a fiscal and regulatory body)) it is important to know something about the survival of the units that integrate the system. In other words, it is relevant to estimate the probability that a CCAM with a given set of characteristics will survive longer than some specified length of time into the future, and identify the characteristics that most contributed to the CCAM insolvency.

The issue of insolvency and causes of its possible occurrence has been studied by several authors, in order to anticipate the processes of restructuring and to reduce the probability of bankruptcy. The first study on insolvency prediction was published in 1932 (Patrick, 1932 apud Kanitz, 1978). However, the topic only flourished in the 1970s with the use of statistical and econometric approaches. In the last four decades several studies have addressed this matter, especially regarding bank failure, but co-operative banks[1] have been neglected (Wilcox, 2010).

The main purpose of this paper is to identify “problematic” CCAM and to evaluate their risk of insolvency as a function of financial indicators, providing regulators and other stakeholders with a set of tools that would be predictive of future insolvency and perhaps bankruptcy. To accomplish this purpose, the paper analyses CCAM failures in the period between 1995 and 2009, using a logistic regression analysis (LRA) and a multiple discriminant analysis (MDA) for assessing the potential failure of CCAM as a function of financial/economical indicators.

The structure of the rest of this paper is as follows. Section 2 frameworks the role of the agricultural credit co-operatives in agricultural development. Section 3 discusses the corporate failure (insolvency) event and offers a brief literature review on failure prediction models and the empirical findings on the failure of financial institutions. Section 4 explains the sample-selection method and describes the data. Section 5 discusses the variables of the model, sample and data used to analyse CCAM failures. Section 6 reports the empirical results and, finally, Section 7 presents the conclusions.

2. Agriculture, co-operatives and agricultural credit in Portugal

The agricultural sector is situated within the framework of the rural economy and the financial markets. Agricultural credit can play a critical role in agricultural development, especially if it is part of a set of other tools to promote this development. The provision of this input is important because credit or loan able funding (capital) is viewed as more than just another resource such as labour, land, equipment and raw materials. It determines access to all of the resources on which farmers depend (Shephard, 1979).

The farm family is typically located in an environment characterized by a number of market failures. A frequent market failure is limited access to credit, a consequence of imperfect and costly information problems encountered in the financial markets. Such problems are known to be particularly important in agriculture (Stiglitz, 1993). Banks perceive agricultural credit as risky, and seek to channel credit to less risky sectors. This behaviour may be due to rational and efficient responses by the lenders to information and contractual problems inherent in agricultural credit markets. As a result of the informational imperfections between the lenders and the borrowers, rationing of credit demand becomes necessary for financial institutions (Stiglitz, 1994). However, credit rationing can be a problem for small farmers and, consequently, a serious constraint to economic growth and social development of poor regions where the agriculture is the main activity.

In addition, the literature highlights the potential ability of co-operative banks to facilitate financial development in a rural area. In a competitive market, joint-stock banks may have few incentives to develop a physical or institutional infrastructure that facilitates the smooth operation of financial intermediation in a rural area (e.g. a branch network), because of the public good nature of information about the quality of potential customers (Hellmann *et al.*, 1997, 2000). That is, if the bank invests, but the quality of the local market is poor, it loses its investment. Even if the quality is high, competitive entry reduces its profit immediately. In contrast, co-operative banks, whose main economic objective is not profit maximization, but the provision of credit services to their members, develop such infrastructures for local financial development at the expense of their own profitability. In addition, it should also be emphasised that in several countries, including Portugal, the area of operation for co-operative banks is geographically restricted directly/indirectly by the government.

In these cases, co-operative banks have no other choice but to take advantage of their own geographically restricted area of operation. For these reasons, it may seem plausible that cooperative banks have potential advantages over their joint-stock counterparts in promoting local economic growth, by delivering more sophisticated financial services in rural areas. In fact, the literature provides strong evidence that local financial development could promote local economic growth (Guiso *et al.*, 2004).

In Portugal, the use of credit dates back a long time, but its wider use developed notably only in the last century. Portugal was a pioneer in the foundation of agricultural credit by creating, in the sixteenth century, charitable institutions and community barns. However, it was only in the beginning of the twentieth century that agricultural credit was established in Portugal on an institutional basis. Until the 1980s agricultural credit was used without any link to other tools which lead to specific goals, because of the lack of consistent policies of agricultural development in Portugal.

Access to agricultural credit has particular relevance in the context of agricultural and rural development, especially, given the country's heavy dependence on imported food products and the present Portuguese sovereign debt crisis. Historically, governments have attempted to overcome agricultural credit constraint problems by subsidizing credit, setting up credit guarantee fund schemes and specialized agricultural credit institutions – the CCAM – and stimulating institutional innovations in the financial system (Santos, 1989).

Since the inception of CCAM, government support has allowed them to play a key role in agricultural development programs. Public entities saw the co-operative as a means of reducing the influence of usurious village moneylenders, while increasing savings and providing easier credit terms to small farmers (Mansinho, 1989). CCAM were originally envisaged as a mechanism for pooling the resources of small producers and providing them with access to different financial services. Democratic in substance, the movement was also an effective instrument of progress in deprived regions, increasing productivity, providing food security and generating employment opportunities in rural areas, thus ensuring social and economic development. Today, the Credito Agricola Group (CA) is a co-operative financial group specialized in agricultural lending and other complementary services, such as insurance, targeting rural and low-income customers. It encompasses 85 local co-operative banks (CCAM) which, in turn, own more than 670 local branches, providing financial services to more than one million customers throughout Portugal.

Recent research questions many of the agricultural credit advantages (Gomes, 2009). The conception of credit as a factor of production instead of the product of financial intermediation ignores an essential property of the financial instrument (is fungible) which allows the separation of the intention of the loan from its effective use. Efficient intermediation reorients evaluation first to the behaviour of savers and investors and last to the performance of the institutions.

Nowadays, the subsidized/cheap agricultural credit policy is under question because it favours the farmers who demand bigger loans and has a high default rates (because of adverse selection and "moral hazard" behaviours) which also debilitates the financial institutions, seriously limiting the contribution of financial markets to agricultural development. Market liberalization and financial politics directed to flexible, more realistic, nominal interest rates seem to be irreversible trends. In this context, the existence of financial institutions, soundly based on their origins, and cultivating "proximity", appears to be a "pro" for the agricultural development process. Here credit co-operatives have a key role to play.

3. The corporate failure event: modelling and prediction

The prediction of corporate failure is important for the firm's stakeholders (shareholders, creditors, staff, managers, regulators, public entities and local community). However, a failure of a firm is something that is not easily predicted, though a company does not collapse before the onset of some economic and financial indicative signs. Economic and financial ratios could be used as a means to the early detection of insolvency.

Different economic and financial indicators have been used to analyse the insolvency of firms, though there is no consensus between authors regarding the definition of insolvency[2] and even the appropriate prediction insolvency models.

The use of bankruptcy prediction models started at the ends of the 1960s and continues to the present time. To study this issue, three different kinds of model have been used:

(1) statistical models (univariate analysis, multiple discriminate analyses and conditional logit regression analyses);

(2) gambler's ruin-mathematical/statistical models; and

(3) artificial neural network models.

Until the early 1980s, MDA was the primary multivariate methodological approach to ratio-based modelling of corporate failure. However, as new statistical tools became available, researchers started testing them with the objective to deriving models that performed as well as MDA, but which relied on fewer assumptions, as the logit regression analysis (LRA) and neural networks. Regardless of the method chosen to compute the results, the majority of them compare with MDA. The Hossari (2007) reviewing corporate failure studies indicates that when MDA is not the main methodology used it is assumed as a benchmark, highlighting its relevance in empirical applications.

In line with other studies, this work uses LRA and MDA[3] for assessing potential failure of CCAM as a function of financial/economical indicators.

3.1 Multiple discriminant analysis

MDA is a statistical technique used to identify the variables which better differentiate (or discriminate) between two or more groups of individuals, structurally different and mutually exclusive, and employs them to create a score (or discriminant function) that parsimoniously represents the differences between groups (Maroco, 2003). It can be used to make predictions in problems where the dependent variable is qualitative (bankrupt or non-bankrupt). To implement the method, initially, are established explicit group classifications and then data are collected taking into account the internal characteristics of the groups. After this procedure, MDA derive a linear combination of these characteristics which "best" discriminates between the groups (Altman, 1968).

In the case under study, if a CCAM has characteristics (financial ratios) which can be quantified for all of the CCAM in the analysis, the MDA determines a set of discriminant coefficients. When these coefficients are applied to the actual CCAM ratios, a basis for classification into one of the mutually exclusive groupings exists. The MDA technique has the advantage of considering an entire profile of characteristics common to the relevant firms, as well as the interaction of these properties (Altman, 1968).

The MDA discriminant function:

$$Z = \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k$$

changes individual variable values to a individual discriminant score or **Z** value which is then used to classify the object, where: $X_1, \ldots, X_k$ are the independent or explanatory variables, and $\beta_1, \beta_2, \ldots, \beta_k$ are the discriminant coefficients. The MDA computes the discriminant coefficients, β_j, while the independent variables X_j are the actual values where, $j = 1, 2, \ldots, k$.

Altman (1968) advises a potentially high degree of correlation or collinearity between some ratios, which requires a careful selection of the predictive variables (ratios) but has the advantage of generating a model with a relatively small number of selected measures with the potential to convey a great deal of information. The main advantage of MDA is its capability to analyse the entire variable profile of the object simultaneously, rather than sequentially examining its individual characteristics. Thus, ratios presenting significant differences between groups, but not of a magnitude to facilitate the development of an accurate prediction model, are excluded.

3.2 Logistic regression analysis

The logit model is a model of qualitative response. It analyses the relationship between dependent (or response) variables and independent (or explanatory) variables.

The dependent variable is always categorical, while the independent variables can be numerical or categorical. These models are applicable to a more extensive set of research situations than MDA (Judge *et al.*, 1985). MDA requires the assumption of multivariate normality of the independent variables and equal variance-covariance matrices in the two groups to obtain an excellent forecast rule. LRA requires fewer assumptions than MDA and, even when the assumptions required by MDA are satisfied, LRA still presents good results (Norusis, 1993). To Lo (1986), MDA and the LRA are equivalent when dealing with models to predict failure.

While, for Laffarga *et al.* (1987) cited by Fully-Bressan (2002) accuracy in predicting a firm's bankruptcy is higher for the LRA model.

MDA specifies a joint distribution of the dependent variable (Yi) and the independent variables (Xi), not only the conditional distribution of Yi given Xi. In qualitative response models, the determination of Xi (CCAM' characteristics) clearly precedes Yi (insolvency). Thus, it is important to specify $\Pr(Yi = 1|X)$, while the specification of the distribution of X can be ignored. On the contrary, in the MDA, Yi precedes the determination of X. In other words, while MDA is a mere technique of classification LRA analyses a causal relation (Janot, 2001).

LRA is used to predict the probability of occurrence of an event by making use of several predictor (independent) variables. In our case, the predictor variables are financial ratios and the aim is to estimate the probability of a given CCAM being insolvent.

The logit model assumes the logistic function functional form:

$$\mathrm{prob}(\mathrm{y_i} = 1) = \frac{1}{1 + \exp^{-xi\beta}}$$

where: Y is a binary variable (assumes the value of 0 or 1); X is the column vector with a $p + 1$ dimension, where p is the number of independent variables; and β is the unknown parametric vector to be estimated. The estimated probability always lies between 0 and 1, independently of the value of $X_i\beta$.

Essentially, the estimation of the logit model intends to generate a set of probabilities. The CCAM which declared insolvency have a higher *ex ante* probability of insolvency compared with the others. A "good adjustment" is a set of coefficients closest to this objective.

With logit regression, it is possible to test the significance of individual estimated coefficients, which is not the case with MDA. Additionally, LRA is more flexible and has a higher statistical power (Lo, 1986).

3.3 Earlier studies of co-operative bank failures

If compared with investor owned bank failures, studies on co-operative bank failures are scarce and use non sophisticated statistical methods (Gordon *et al.*, 1987; Gordon, 1991; Shafroth, 1997). Exceptions are Kharadia and Collins (1981) and Kane and Hendershott (1996) that use OLS and logit, respectively, to model credit union failures.

More recently, Maggiolini and Mistrulli's (2005) survival analysis studies the features of Cooperative Credit Banks (CCBs) established in Italy during the 1990s. The authors found that duration is positively related to the market share of large banks and is higher when there are no incumbent CCBs in the same market. Survival probability is directly related to the local level of GDP. Fiordelisi and Mare (2011), using a discrete time survival model, show that efficiency has a positive link with the probability of survival of co-operative banks.

Studies by Fully-Bressan (2002), Fully-Bressan *et al.* (2004), Braga *et al.* (2006) and Carvalho *et al.* (2009) focused on Brazilian credit co-operatives. The first two studies employed a logit and Cox proportional hazard model. Their results suggest that the relevant indicators for insolvency prediction are capitalization, volunteer covering and fund-raising growth, and, for relative risk analysis, liquidity, short run disposable resources and labour cost. Braga *et al.* (2006) using a Cox proportional hazard model indicated that the relevant indicators for insolvency prediction were, in descending order of predictive ability, general liquidity, salary and benefit expenses, and loan/equity ratio. Finally, Carvalho *et al.* (2009) used both logit and Cox proportional hazard models and concluded that credit co-operative mortality depends on their size and operational efficiency.

Some studies investigate the failure of co-operative and non co-operative financial institutions. Schaeck and Wolfe (2005) develop early warning indicators for banking difficulties, using a parametric approach. These authors' findings indicate that co-operatives are more prone to experience financial difficulties than savings banks. Wilcox (2005) compares credit unions and commercial banks and reports that, among credit unions, smaller asset size, lower capital, higher loan-to-asset ratios, higher non-interest expenses, and more delinquent loans were associated with lower failure rates. Beck *et al.* (2009) assessing the stability of German banks using three different measures of bank stability – the *z*-score, a standard measure of distance from insolvency, non-performing loans, and distress probabilities derived from hazard models – find consistent evidence that privately-owned (IOF) banks are less stable than government-owned savings banks and co-operative banks.

Furthermore, co-operative banks are farther away from insolvency than government-owned savings banks, but are more likely to become distressed than savings banks. The authors also find evidence for the Too-Big-To-Fail phenomenon, as larger IOF banks hold less risk-weighted capital than their smaller peers, thus moving closer to insolvency, but face lower distress probability. Co-operative or savings banks are more stable if larger.

Wilcox (2010) presents the first large-scale, long-term (1981-2005) econometric analysis (logit and OLS) of commercial bank and credit union failures. The author concludes that the behaviour and operating procedures that foretell credit union and bank failures are different. The variables traditionally used to analyse commercial bank failures (smaller asset size, higher ratios of net loans, commercial and industrial loans, provisions for loan losses, delinquent loans, non-interest expenses, higher state unemployment rates, lower ratios of capital and return on assets) are useful in analysing credit union failures, but most individual variables have coefficients statistically different, varying the value and level of significance of the parameters between banks typology, assets and along the time.

4. Data and sample

4.1 The CCAM failure event

The agricultural co-operative credit system in Portugal is made up of an integrated system (SICAM) of two types of co-operatives: the central and the individual (associated) in a regime of co-responsibility. SICAM = Central CCAM + Associated CCAM (85 local CCAM). Figure A1, in the Appendix, gives an overview of the SICAM and Credito Agricola Group.

Now celebrating their 100th anniversary, Portuguese credit co-operatives had a tough birth and a difficult childhood: mismanagement, lack of funds and political control and interference resulted in a fairly inactive life until the 1980s of last century. Following the 1974 political changes and the entry of Portugal into the European Union in 1986, CCAM experienced a spectacular growth in their activity, as they were considered an important factor in the framework of a financing strategy for the development of the agricultural sector. But this was a period of euphoric growth and disorganization.

During the 1990s the financial imbalance, that touch most of the 211 CCAM, began to be resolved via a merging process driven by SICAM. The root of this strategy is a report prepared by SICAM, based on 1992 data, which concludes that to generate consistent net benefits a typical CCAM must have deposits up to €70 million, a value not achieved by 96.6 per cent of CCAM (Cabo, 2003). Despite these initial circumstances, only few CCAM went bankrupt and nowadays SICAM has a significant position in the Portuguese banking system, especially, regarding employment, branches network and total deposits, being one of the most robust entities operating within it, with an excellent position with regard to efficiency, solvency, liquidity, and customer claims (Cabo and Rebelo, 2010). These results derive above all from two main factors: the intense restructuring process carried out within SICAM and SICAM governance structure and control mechanisms.

The restrictions on individual growth imposed by the local nature of CCAM[4] and the lack of funding and time led SICAM decision makers to assume an intense process of merging and restructuring, financially supported by the Insurance Fund of Agricultural Co-operative Credit (FGCAM). The changes are so intense that, in ten years, CCAM's average assets increased more than fourfold and in 2010 the number of CCAM was reduced to 85. This strategy not only "saved" distressed CCAM from bankruptcy as also provided CCAM with the operational conditions to compete efficiently in a changing and challenging banking market.

SICAM establishes a regime of co-responsibility between Central CCAM and its associates. Central CCAM guarantees its associates without limitations and is also guaranteed by them. SICAM is, in this way, subordinated to a double guardianship. Furthermore, when a CCAM gets into financial distress, the Central CCAM has an incentive to protect this CCAM from default because it is important to maintain the high reputation of the whole CCAM system and the confidence of its different stakeholders.

Within SICAM, management control is often exercised by Central CCAM whose power is to orientate and supervise, and, consequently is the first to detect managerial failures. In cases of gross mismanagement or fraud, CCAM governing bodies can be formally dismissed by Central CCAM. Indeed, Central CCAM is empowered to intervene in the associates, by the assignment of a representative to monitor CCAM management or by the nomination of provisory directors whenever it verifies an imbalance situation which, because of its extension or continuity, can jeopardize the daily running of the CCAM, its solvency is at risk or serious irregularities occur.

Long-term inefficiencies are often resolved through "obligated"[5] mergers with another (more efficient) CCAM. Additionally, the FGCAM, as was as the assuring of CCAM customers' deposit promotes SICAM solvency and liquidity and, therefore, performs an active role in the economic and financial restructuring process of SICAM, offering financial support in the form of subordinated loans. Rescuing operations by FGCAM are conditional on an economic and financial restructuring process which often includes the merger with (or incorporation into) more efficient CCAM.

4.2 Sample

The period under study is 1995-2009 and includes the CCAM associates of SICAM, a pooled of 1,827 observations. The financial data are collected from annual accounting reports and the non-financial data (CCAM mergers and incorporations, Central CCAM interventions, and others) from "Diario da Republica[6]", Ministry of Justice web site, CCAM annual reports and other SICAM official statements released during the study period.

The profound SICAM restructuring process reduced the number of CCAM from 190, in 1995, to just 85, in 2009, only 40 per cent of which are considered solvent. The 1,827 observations of the sample are divided in two groups: group 1 has 1,315 observations and is made up of solvent CCAM, i.e. those that did not become insolvent during the study period; group 2, with 512 observations, are CCAM that become insolvent in the study period. Table AI in the Appendix provides summary statistics.

Most studies of bankruptcy use matching samples composed of pairs of bankrupt and nonbankrupt firms. This procedure clearly introduces much sample-selection bias (Zavgren, 1985; Lo, 1986) and, therefore, was not followed in this paper. The choice of a 15-year period is not the best procedure, since average ratios shift over time. Ideally we would prefer to examine a list of ratios in time 1 in order to make predictions about other CCAM in the following period, time 2. Unfortunately it was not possible to do so because of data limitations. However, the number of insolvencies was more-or-less evenly distributed over the 15-year period, thus minimizing its effects on estimations.

5. Model and variables

5.1 Model

A general model of CCAM insolvency is estimated following the failure model in equation (1):

$$Fail_{it}^{*} = \beta_i' X_{it} + u_{it} \tag{1}$$

where:

$$Fail_{it} = 1 \ \text{ if } Fail_{it}^{*} \geq 0; \ \ Fail_{it} = 0 \ \text{ otherwise}$$

The dependent variable, $Fail_{it}$, takes a value of 1 if the insolvency requirement is met. Otherwise, $Fail_{it}$ takes a value of 0. The X_{it} variables used to predict bankruptcy are financial and operating ratios.

In the iterative way of the modelling process, a core group of predictors was developed to which additional predictors were added individually. The core set of variables expands as additional factors yield a coefficient with the expected sign, statistical significance, and improved classification accuracy. This approach concentrates on the explanatory power of variables. The selection of the final set of financial and operating ratios was based on their conformity to a priori sign expectations, the statistical significance of estimated parameters and on model classification results.

Methodologically is followed a two-step procedure. Initially, the 1995-2010 data were used to categorize CCAM by status: solvent and insolvent group. CCAM is considered insolvent when it is positive on one insolvency test. In contrast, a CCAM is categorized as solvent otherwise. Then financial ratios are computed with earlier data from 1994[7]-2009. Finally, these ratios are used to predict insolvency.

5.2 Variables

As stated, it is not usual to see a CCAM bankruptcy. Over the period of analysis (1995-2009), only five CCAM went bankrupt and their assets went transferred to other CCAM. But consulting the sample's financial data for the year 1995 shows that almost 30 per cent of the CCAM present negative equity, and, additionally, 20 per cent more are severely financially distressed and restructuring at FGCAM request. Thus, half of the CCAM, although still operating, are insolvent and, without SICAM support, this would certainly be their end. Indeed, only one of the five bankrupt CCAM belongs to the above-mentioned insolvent group.

Because of this small number of CCAM which went bankrupt as defined, it was necessary to refine the definition of "insolvent" to better illustrate the CCAM case. Thus, it is adopted a multidimensional interpretation of insolvency in which a CCAM is categorized as insolvent if it meets at least one of the following criteria in a given year:

- presents negative equity;
- is subjected to a Central CCAM intervention or FGCAM[8] restructuring operation;
- is incorporated into (or merged with) another CCAM; and
- is bankrupt for any reason.

Using the four separate insolvency definitions, more CCAM are labelled as insolvent than would be the case with an individual screen. That is, it is more likely that a non-insolvent CCAM is labelled as insolvent; though, as a consequence, more insolvent CCAM may be correctly described. This outcome is preferred when the cost of misidentifying a non-insolvent CCAM as insolvent is lower than the alternative misclassification. Insolvent CCAM in period t were defined as those that comply with at least one of the screening criteria in t + 1 period and non-insolvent CCAM otherwise.

As explanatory variables a set of financial ratios is used, created from the balance sheet data of the 1994-2009 period. The choice of variables was based on the authors' previous studies regarding CCAM and from a review of the literature on insolvency. The financial ratios represent measures of profitability, leverage, liquidity, operating efficiency and growth, all of them being variables frequently included in models for predicting financial distress or bankruptcy.

Table I shows the financial ratios which were tested as independent variables for modelling purposes. Table AI in the Appendix offers the variables summary statistics.

The literature on corporate failure provides an extensive battery of ratios helpful to understand and predict this event. While taking these into consideration, the limitations imposed by the data available and CCAM particularities guided our selection. CCAM are under a special regime, essentially because of their co-operative form and their priority goal of performing agricultural credit operations in favour of their members. They are specialized credit institutions subjected to various restrictions imposed by law, namely, territorial area and authorized operations.

Credit intermediation is the core business of banking activity, and for CCAM this is especially true. Despite CCAM efforts to diversify their net worth portfolio, favouring a cross-selling strategy of insurance and investment products, Financial Margin is still CCAM's main source of income. A decade ago Financial Margin contribution to net worth was around 90 per cent, currently it is reduced to 75 per cent, but is still 15 points above

Table I. Variable definitions and transformations

Group 1 – operational efficiency and growth

$$\text{Intermediation Function ratio} = \frac{\text{Financial Margin}^{a}}{\text{Net Profit}}$$

$$\text{Transformation ratio} = \frac{\text{Total Loans}}{\text{Costumer Deposits}}$$

$$\text{Credit Overdue} = \frac{\text{Credit Overdue}}{\text{Gross Credit}}$$

$$\text{Credit Growth} = \frac{\text{Gross Credit in time t}}{\text{Gross Credit in time t} - 1} - 1$$

$$\text{Customer Resources Growth} = \frac{\text{Customer Deposists in time t}}{\text{Customer Deposits in time t} - 1} - 1$$

Group 2 – cost efficiency

$$\text{Expenses ratio} = \frac{\text{Total Expenses}}{\text{Total Revenue}}$$

$$\text{Labours Costs} = \frac{\text{Salary and Benefit Expenses}}{\text{Financial Margin}}$$

$$\text{Structural Costs} = \frac{\text{Administrative Expenses}^{b}}{\text{Financial Margin}}$$

Group 3 – leverage and liquidity

$$\text{Liquidity} = \frac{\text{Net Cash in Central Banks \& other credit intitutions}}{\text{Total Liabilities}}$$

$$\text{Cash Flow} = \frac{\text{Net Profit} + \text{Amortisation} + \text{Net Provisions}}{\text{Total Assets}}$$

$$\text{Indebtedness} = \frac{\text{Total Debt}}{\text{Total Assets}}$$

$$\text{Debt to Equity ratio} = \frac{\text{Total Liabilities}}{\text{Equity}}$$

Group 4 – return ratios

$$\text{ROA} = \frac{\text{Net Profit}}{\text{Total Assets}}$$

$$\text{ROSC}^{c} = \frac{\text{Net Profit}}{\text{Shareholders Capital}}$$

$$\text{Financial Margin} = \frac{\text{Financial Margin}}{\text{Total Assets}}$$

Notes: [a]Net interest and other similar income; [b]costs of general services incurred in controlling and directing an organization, such as accounting, energy and water supply, advertising, office resources expenses, etc.; [c]the option for shareholders capital instead of equity is justified by the existence of CCAM with lower equity resulting from previous years accumulated losses which can jeopardize the results of the study that of the overall banking system. This double specialization (in customers served and products offered) is a serious constraint in modern Portugal, where rural exodus is on-going, the population is concentrated in coastal urban areas and agriculture is in decline. In face of this, special care was given to the intermediation function and credit management activity. Intermediation Function Ratio measures the importance of Financial Margin to CCAM returns; a CCAM less dependent on this source of income lowers its risk by diversifying. Additionally, the decline of spreads is reducing CCAM earnings. Transformation and Credit Overdue ratios aim to capture CCAM credit management risk.

CCAM are saver, not loaner institutions, with a prudential lending policy. This strategy, despite sacrificing short term net benefits, has proved to be the correct one in the long term, as the current financial crisis illustrates. A high Transformation Ratio maximizes CCAM revenues (and, thus, CCAM returns) but can also put the CCAM in a vulnerable situation, facing Credit Overdue and liquidity distress, especially in periods of economic recession, when borrowers have more difficulty in recovering their credit, and with interbank competition for funds remaining intense, as in the present economic and financial crisis. Thus, an aggressive lending policy is a high-return, high-risk strategy. A profound knowledge of market conditions and of their customers, based on the concept of proximity as in the CCAM case, is essential for success when adopting this strategy. Therefore, Transformation Ratio influence on CCAM failure is unpredictable. Credit Overdue is expected to have a positive influence on CCAM failure probability. Credit and Customer Resources Growth ratios are measures of CCAM competitive strength and market share and should present a negative influence.

Banking is a highly demanding activity, where cost efficiency is crucial for success. Thus, excessive expenditure will certainly result in financial troubles. As a rule, the expenditure items must always be under CCAM management control. Expenses Ratio, Labour Costs and Structural Costs ratios are measures of CCAM cost efficiency, of its ability to exploit scale economies and to rationalize expenses, particularly of CCAM management and organizational structures. These ratios are expected to positively influence CCAM probability of failure.

Indebtedness and debt to equity ratios are measures of CCAM level of capitalization and leverage. Given their non-profit nature, equity is the cheaper CCAM financing source; although it is difficult to CCAM obtain equity since they cannot publicly do so.

Liquidity reflects the means available to CCAM to answer short term debt. A lack of liquidity indicates that CCAM can experience problems in performing its daily operations. A credit institution with "no money" is on track to failure. On the other hand, the CCAM legal regime in practice limits CCAM financial applications to deposits in other credit institutions. Thus, contrary to other Portuguese IOF banks, CCAM excess of liquidity can be a real problem, particularly at present, as the 2009 accounts show. Indeed, European Central Bank measures to respond to the liquidity shortfalls of a number of institutions (starved of funds as the refinancing markets seized up in the crisis) severely affect CCAM operating conditions:

> In fact, the impact of the policy was much more negative for us than the crisis itself [...] With euribor rates hitting a very low point, the Group's operating conditions bore the brunt, both in the local Caixas and at the Caixa Central, since a very large part of the credit portfolio is based on an interest rate structure linked to these market references. Moreover, the profitability of the Group's liquidity reserves was also stunted by the unnecessarily low interest rate policy (Crédito Agrícola, 2010, p. 6).

A positive influence of liquidity ratio on CCAM failure probability would not be a surprise.

Finally, the ratios in the fourth group, the profitability ratios, are expected to present a negative influence on CCAM failure probability. For CCAM, profit is not an end but a means for survival. Despite being non-profit institutions, CCAM survival depends on their ability to generate net returns to support their capital needs. However, if the insolvent CCAM suffer from a profounder income specialization than the solvent ones (and the authors' understanding of the CCAM reality suggests this), Financial Margin ratio can present a positive influence on CCAM failure probability.

Table II includes the expected signs of the coefficients of the variables that can influence the probability of CCAM failure.

6. Results

To determine which of the 15 explanatory variables presented in Table I, are the best predictors of failure, following the same procedure as Janot (2001), a stepwise procedure combining forward and backward elimination is applied. The model starts as a baseline model without any variable on it. The 15 indicators are considered one at a time, and added to the model if succeeding in the selection criterion based on a p-value of 5 per cent. When a new variable is added to the model, the variables previously included are evaluated for exclusion, at 10 per cent significance level. The ones which fail are excluded. When no more variables can be added or removed, the algorithm stops.

The stepwise procedure within the logistic regression and MDA selects among the independent variables the ones that contributed more to the CCAM insolvency and calculates the insolvency probability of each CCAM. If that probability is greater than 0.5 the model classifies the CCAM as insolvent, otherwise, as solvent. When comparing this classification with the observed status of the CCAM two types of error can occur: Type I error occurs when the model classifies as solvent a CCAM that became insolvent during the period analysed; Type II error occurs when the model classifies as insolvent a solvent CCAM. The greater the model accuracy, the more efficiency it presents in predicting CCAM failure.

In order to better assess the model accuracy, the sample (1,827 observations) was divided and approximately 70 per cent of the insolvent CCAM were randomly selected and used to create the models. The remaining insolvent CCAM were used to validate the model results.

The variable Total Assets was added to both models to control for CCAM size.

Group 1 – operational efficiency and growth		*Group 2 – leverage and liquidity*	
1. Intermediation Function Ratio	+	1. Liquidity	±
2. Transformation Ratio	±	2. Cash Flow	−
3. Credit Overdue	+	3. Indebtedness	+
4. Credit Growth	−	4. Debt to Equity Ratio	+
5. Customer Resources Growth	−		
Group 3 – cost efficiency		*Group 4 – return ratios*	
1. Expenses Ratio	+	1. ROA	−
2. Labour Costs	+	2. ROSC	−
3. Structural Costs	+	3. Financial Margin	±

Table II. Expects signs of variable coefficients

6.1 Logit model

The LRA, using the forward stepwise method[9] with the likelihood ratio statistics, selected only six of the 15 variables used in the estimation as predictors of CCAM failure. Table III reports the results for the logit model.

All the coefficients have the expected signs. The unique surprise is the absence of a profitability variable (ROA and ROCS). The Nagelkerke pseudo R^2 statistic[10] is 0.626.

The results show that CCAM failure is more likely when the CCAM presents an increase in Credit Overdue. Similarly, the positive sign on Expenses Ratio and Structural Costs ratio implies that an improvement in cost efficiency is correlated with a fall in the probability of failure. Another important determinant of CCAM failure is indebtedness, confirming its positive sign the importance of equity funds to CCAM in order to assure their financial autonomy. Finance experts often suggest that a corporation may increase its leverage ratio by borrowing money. The more it borrows the less equity capital it needs, so any profits or losses are shared among a smaller base and are proportionately larger as a result. Co-operative leaderships facing difficulties in increasing CCAM equity often prefer to deal with an outside creditor instead of implementing strategies to increase members' shareholdings. This policy has higher financial costs, diminishing the co-operative net returns and, in the long run, jeopardizes survival. Finally, the positive sign of the Financial Margin coefficient confirms the hypothesis that higher concentration in income sources increases the probability of CCAM failure.

The accuracy in classification indicates how well the model performs. A good model should correctly identify a higher percentage of cases. Classifications based upon the cases used to create the model tend to be too "optimistic", in the sense that their classification rate is inflated. Subset validation is obtained by classifying insolvent CCAM that were not used to create the model. Table IV show the result of applying the model for the prediction of CCAM failure to the sample of CCAM used in the model estimation, and to the unselected ones.

From the cases used to create the model, 912 of the 944 solvent CCAM are classified correctly and 238 of the 363 insolvent CCAM are classified correctly. Overall, 88 per cent of the cases are classified correctly. The results in the unselected cases show that 87.6 per cent of these cases were correctly classified by the model. This result suggests that, overall, the model is correct about four out of five times.

As mentioned earlier, Type II error occurs when the model classifies as insolvent a solvent CCAM. This error results in misdirecting resources to assist a CCAM which is not in need of them. The model incurs this fault less than 4 per cent, overall. Type I error occurs when the model classifies as solvent a CCAM that became insolvent during the period analysed. The logit model misclassifies approximately one-third of the insolvent CCAM:

Table III.
LRA coefficients and significance level

Variable	B	SD	Significance level
Constant	−33.408	2.459	0.000
Customers Resources Growth	−3.976	1.178	0.001
Credit Overdue	4.228	1.471	0.004
Expenses Ratio	2.127	0.453	0.000
Structural Costs	1.444	0.591	0.015
Indebtedness	30.536	2.568	0.000
Financial Margin	26.474	3.718	0.000
Total Assets	0.000	0.000	0.020

34.4 per cent of the selected cases and 34 per cent of the unselected. This is a far worse result, especially because it is a more costly error. The failure to signal a potentially insolvent CCAM leaves it out of vigilance and no correction measures will be adopted to prevent the failure. This is an error that jeopardizes the value of the model as an early system warning.

Having developed a logit model of failure, the analysis turns to consider the results from MDA, so as to evaluate whether there are gains in predictive accuracy from using logit rather than MDA.

6.2 Discriminant analysis model

Table V reports the results for the MDA model. If compared with the logit model, MDA model presents some differences. It selected two additional variables as predictors of CCAM failure: Transformation Ratio and liquidity.

The results are similar to the ones obtained by the logit model for the variables selected by both methods. The coefficient for Customer Resources Growth is smaller for Yes classification function, which means that CCAM with more ability to attract customer resources are less likely to fail. Similarly, CCAM with greater Credit Overdue, Expenses and Structural Costs ratios and Indebtedness are more likely to fail. The new variables added by MDA, Transformation Ratio and Liquidity, present both a positive influence on the probability of failure. The coefficient for Transformation Ratio is smaller for Yes function, which means that CCAM with a more aggressive lending policy are less likely to fail. As mentioned earlier this is a less risk-adverse strategy, not usual in co-operative credit and, thus, this result is somewhat surprising. Liquidity coefficient also indicates that CCAM with higher liquidity are less likely to fail. Despite the low return

		Predicted					
		Selected cases			Unselected cases		
		Failure			Failure		
	Observed	No	Yes	Percentage	No	Yes	Percentage
Failure	No	912	32	96.6	357	14	96.2
	Yes	125	238	65.6	50	97	66.0
	Overall percentage			88.0			87.6

Notes: [a]Cut value is 0.5; cells on the diagonal are correct predictions; cells off the diagonal are incorrect predictions

Table IV.
CCAM classification[a] by the LRA

	Failure	
	No	Yes
Constant	−25.835	−31.421
Customer Resources Growth	8.447	7.016
Transformation Ratio	35.550	33.724
Credit Overdue	−13.881	−2.789
Expenses Ratio	5.787	6.915
Structural Costs	1.120	1.307
Liquidity	4.491	3.594
Indebtedness	19.832	22.902
Financial Margin	47.139	63.077
Total Assets	2.93×10^{-008}	3.35×10^{-008}

Table V.
MDA classification function coefficients

options available to CCAM to apply their liquidity surplus; MDA prove that more is still better in the case of liquidity.

To sum up, insolvent CCAM have high Credit Overdue scores, and low rates of customers' resources growth and low ability to convert deposits on loans. They are cost inefficient, with a high relation between expenses and revenues generated, and heavy Structural Costs. Moreover, they experience liquidity pressure; a weighty dependence on outside capital to finance their operations and a low level of revenue diversification.

Consulting the logit model results, it is expect that the new variables selected by MDA can contribute to a better understanding of CCAM failure and, so, the MDA model should have better score in the validation phase. Table VI shows the model performance in predicting CCAM failure.

From the cases used to create the model, 842 of the 944 solvent CCAM are classified correctly and 213 of the 363 insolvent CCAM are classified correctly. Overall, 80.7 per cent of the cases are classified correctly. The results in the Unselected Cases show that 81.5 per cent of these were correctly classified by the model. This is a slightly worse result than the logit model. The real problem, Type I error, is somewhat inflated by this model. MDA model misclassifies almost 40 per cent of the insolvent CCAM: 41.3 per cent of the selected cases and 37.4 per cent of the unselected.

Overall logit and MDA models excel at identifying solvent CCAM. However, it does a poor job in classifying insolvent CCAM. Further investigation is needed to find another predictor in order to better explain CCAM failure event.

Having developed two models of failure, the analysis turns to consider the results from both to evaluate whether there are gains in predictive accuracy from using logit rather than MDA.

Despite the contribution of two additional variables the MDA model is rejected in favour of the higher accurate logit model[11].

7. Conclusion

The CCAM failure models presented identified: Customer Resources Growth, Transformation Ratio, Credit Overdue, Expenses Ratio, Structural Costs, Liquidity, Indebtedness and Financial Margin as determinants of CCAM failure. These results require that CCAM take measures geared to boosting business, to shoring up the Financial Margin and the deposit base, to bolstering the complementary margin and to improving the credit recovery processes. Additionally, it is necessary to increase cost efficiency, by rationalizing structures and procedures consistent with reducing operating costs, without detriment to the quality of service provided.

Table VI.
CCAM classification[a] by the MDA model

		Predicted					
		Selected cases			Unselected cases		
		Failure			Failure		
	Observed	No	Yes	Percentage	No	Yes	Percentage
Failure	No	842	102	89.2	330	41	89.9
	Yes	150	213	58.7	55	92	62.6
	Overall percentage			80.7			81.5

Notes: [a]Cut value is 0.5; cells on the diagonal are correct predictions; cells off the diagonal are incorrect predictions

The low performance of the models in the identification of insolvent CCAM, points to the need for more research to identify other predictor variables that would better classify these CCAM. Additionally, the adoption of a blind rule in the CCAM classification can lead to potential misclassification and this is a question that deserves further attention. The particularities of SICAM governance and control mechanism, and the change in CCAM operating conditions can raise the question about the definition of insolvency used in this paper, especially regarding Central CCAM interventions and the merger or incorporation indicators. The sample contains 115 merged/incorporated CCAM classified as insolvent. It is logical to assume that not all of them were near to a bankruptcy state when engaged in merger activity. A deeper understanding of the each merger/incorporation circumstances could help to avoid the risk of misclassification.

Notes

1. In this paper the term "co-operative bank" includes also saving and credit co-operatives and credit unions.
2. For Emmery and Finnerty (1997), insolvency occurs when a firm is not able to pay its debts. Altman (1968) considers that insolvency occurs when the shareholders receive profitability lower than alternatives supplied by the market under similar conditions. Matias and Siqueira (1996) classified a bank as insolvent if it was under intervention or in liquidation by the supervising entity. For Janot (2001) a firm becomes insolvent when it presents negative equity or if it is impossible to continue operating without incurring losses that would result in negative equity. This author also defines it as insolvent when an institution is placed under evidence by the supervising authorities. He concludes that the identification of a financial institution as a likely candidate for failure by bank regulatory agencies is a signal of insolvency.
3. These methods have also been used to estimate credit scoring models (Dunn and Frey, 1976; Lufburrow *et al.*, 1984; Turvey, 1991; Altman and Franco, 1994; Turvey and Weersink, 1997; Barney *et al.*, 1999).
4. The CCAM' activity is restricted to the county ("concelho") where it is located, i.e. the CCAM are regional organizations and their product markets are limited.
5. Although mergers are friendly (they must be approved by the general meeting) the influence of Central CCAM is considerable, being this top institution the trigger and even the one that choose the merger partners (Cabo and Rebelo, 2005).
6. It is the Portuguese Government official journal.
7. Data from 1994 were also collected to allow measurement of growth rates from 1994 to 1995.
8. A CCAM is considered potentially insolvent if benefits of FGCAM subordinated loans greater than 50 per cent of equity.
9. The logit model was also estimated with all variables included and tested against the step wise model by a (χ^2 test (difference between -2LL models) results show that the step wise model holds statistically at 0.1 significance level.
10. Pseudo R^2 statistic has similar properties to the true R^2 statistic and measures the variability in the dependent variable. The pseudo R^2 statistics are based on comparing the likelihood of the current model to the "null" model (one without any predictors). Larger pseudo R^2 statistics indicate that more of the variation is explained by the model, from a minimum of 0 to a maximum of 1.
11. This achievement is based on the logit model re-estimation including all of the selected DM variables. The χ^2 test (difference between -2LL models) is applied to test if the hypothesis that the coefficients of the variables added are simultaneously 0 and it cannot reject the null hypothesis, at 0.1 of significance level, thus, indicating that the smallest model holds statistically.

References

Altman, E. (1968), “Financial ratios, discriminant analysis and the prediction of corporation bankruptcy”, *Journal of Finance*, Vol. 23 No. 4, pp. 589-609.

Altman, E. and Franco, P. (1994), “Corporate distress diagnosis: comparisons using linear discriminant analysis and neural networks (the Italian experience)”, *Journal of Banking & Finance*, Vol. 18, pp. 505-29.

Barney, D., Graves, O. and Johnson, J. (1999), “The farmers home administration and farm debt failure prediction”, *Journal of Accounting & Public Policy*, Vol. 18, pp. 99-139.

Beck, T., Hesse, H., Kick, T. and von Westernhagen, N. (2009), “Bank ownership and stability: evidence from Germany”, working paper.

Braga, M., Fully Bressan, V., Colosimo, R. and Bressan, A. (2006), “Investigating the solvency of Brazilian credit unions using a proportional hazard model”, *Annals of Public and Co-operative Economics*, Vol. 77 No. 1, pp. 83-106.

Cabo, P. (2003), *As Fusões no Sistema Integrado de Crédito Agrícola Mútuo*, University of Minho, Braga.

Cabo, P. and Rebelo, J. (2005), “Why do agricultural credit co-operatives merge? The Portuguese experience”, *Annals of Public and Co-operative Economics*, Vol. 76 No. 3, pp. 491-516.

Cabo, P. and Rebelo, J. (2010), “Ownership and governance of Portuguese credit co-operatives: the legal framework”, paper presented Lyon’ ICA European Research Conference, “Co-operatives Contributions to a Plural Economy”, Lyon, 2-4 September.

Carvalho, F., Kalatzis, A., Diaz, M. and Neto, S. (2009), “Mortalidade e Longevidade de Cooperativas de Crédito Brasileiras: uma Aplicação dos Modelos Logit e de Riscos Proporcionais de Cox”, 9th Congresso USP Controladoria e Contabilidade: Da pesquisa que temos para a pesquisa que precisamos, School of Economics, Business and Accounting, University of São Paulo, São Paulo, 30-31 Jully.

Crédito Agrícola (2010), *Crédito Agrícola Report and Consolidated Accounts 2009*, Crédito Agrícola, Lisbon.

Dunn, D. and Frey, T. (1976), “Discriminant analysis of loans for cash grain farms”, *Agricultural Finance Review*, Vol. 36, pp. 60-6.

Emmery, D. and Finnerty, J. (1997), *Corporate Financial Management*, Prentice-Hall, Upper Saddle River, NJ.

Fiordelisi, F. and Mare, D. (2011), “Efficiency and probability of default in co-operative banking”, 28 February, available at: http://ssrn.com/abstract=1776423; http://dx.doi.org/10.2139/ssrn.1776423

Fully-Bressan, V. (2002), *Análise de Insolvência das Cooperativas de Crédito Rural do Estado de Minas Gerais*, Federal University of Viçosa, Viçosa.

Fully-Bressan, V., Braga, M. and Bressan, A. (2004), “Análise do Risco de Insolvência Pelo Modelo de Cox: uma Aplicação Prática”, *RAE – revista de administração de empresas*, Vol. 44, p. 2004, Edição Especial, abr-dez.

Gomes, A. (2009), “Captação de Poupanças em Meio Rural, Estudo de Casos na área social da Caixa de Crédito Agrícola Mútuo da Costa Azul”, Master dissertation, ISA, Technical University of Lisbon, Lisbon.

Gordon, D. (1991), “Source of losses to the National Credit Union Share Insurance Fund”, Research Study No. 15, NCUA Office of the Chief Economist, National Credit Union Administration, Washington, DC.

Gordon, D., Solt, M. and Bradford, C. (1987), "Causes of credit union failures 1981-85", Research Study No. 4, NCUA Office of the Chief Economist, National Credit Union Administration, Washington, DC.

Guiso, L., Sapienza, P. and Zingales, L. (2004), "Does local financial development matter?", *Quarterly Journal of Economics*, Vol. 119 No. 3, pp. 929-69.

Hellmann, T., Murdock, K. and Stiglitz, J. (1997), "Financial restraint: toward a new paradigm", in Aoki, M., Kim, H.K. and Okuno-Fujiwara, M. (Eds), *The Role of Government in East Asian Economic Development: Comparative Institutional Analysis*, Oxford University Press, New York, NY.

Hellmann, T., Murdock, K. and Stiglitz, J. (2000), "Liberalization, moral hazard in banking, and prudential regulation: are capital requirements enough?", *American Economic Review*, Vol. 90 No. 1, pp. 147-65.

Hossari, G. (2007), "Benchmarking new statistical techniques in ratio-based modelling of corporate collapse", *International Review of Business Research Papers*, Vol. 3 No. 3, pp. 141-216.

Janot, M. (2001), "Early warning models of banking failures in Brasil", Banco Central do Brasil Working Paper No. 13.

Judge, G., Griffiths, W., Hill, R., Lutkepohl, H. and Lee, T. (1985), *The Theory and Practice of Econometrics*, 2nd ed., Wiley, New York, NY.

Kane, E.J. and Hendershott, R. (1996), "The federal deposit insurance fund that didn't put a bite on US taxpayers", *Journal of Banking & Finance*, Vol. 20, pp. 1305-27.

Kanitz, S. (1978), *Como prever falências*, McGraw-Hill, São Paulo.

Kharadia, V.C. and Collins, R.A. (1981), "Forecasting credit union failures", *Journal of Economics and Business*, Vol. 33 No. 2, pp. 147-52.

Lo, A. (1986), "Logit versus discriminant analysis", *Journal of Econometrics*, Vol. 31, pp. 151-78.

Lufburrow, J., Barry, P.J. and Dixon, B.L. (1984), "Credit scoring for farm loan pricing", *Agricultural Finance Review*, Vol. 44, pp. 8-14.

Maggiolini, P. and Mistrulli, P. (2005), "A survival analysis of de novo co-operative credit banks", *Empirical Economics*, Vol. 30, pp. 359-78.

Mansinho, M.A. (1989), "Politicas de Crédito Agrícola: Atribuição e Recuperação de Fundos. Melhoramentos Agrícolas 1946-1979", PhD thesis, ISA, Technical University of Lisbon, Lisbon.

Maroco, J. (2003), *Análise estatística com utilização do SPSS*, 2nd ed., Edições Sílabo, Lisboa.

Matias, A. and Siqueira, J. (1996), "Risco bancário: modelo de previsão de insolvência de bancos no Brasil", *Revista de Administração*, Vol. 31 No. 2, pp. 19-28.

Norusis, M.J. (1993), *SPSS for Windows: Advanced Statistics*, Release 6.0, SPSS Inc., Chicago, IL.

Santos, S. (1989), "O Crédito como Instrumento de Política Agrícola. Sua Integração no Mercado Financeiro Rural, O caso português visto do lado da oferta", Master dissertation, Technical University of Lisbon, Lisbon.

Schaeck, K. and Wolfe, S. (2005), "Identifying 'problem banks' in the German co-operative and savings bank sector: an econometric analysis", paper presented at MMF 2005: 37th Annual Conference of the Money, Macro and Finance Research Group, Crete, Greece, 1-3 September.

Shafroth, M. (1997), *An Analysis of Unexpected Credit Union Failures in 95 and 96*, CUNA Economics & Statistics, Madison, WI.

Shephard, W. (1979), *Market Power and Economic Welfare*, Random House, New York, NY.

Stiglitz, J. (1993), "Incentives organisational structures and contractual choice in the reform of socialist agriculture", in Beaverman, A., Brooks, K. and Csaki, C. (Eds), *Agricultural Transition in Central and Eastern Europe and Former USSR*, The World Bank, Washington, DC.

Stiglitz, J. (1994), "The role of the state in financial markets", *Proceedings of the World Bank Conference on Development, 1993, Supplement to World Bank, World Bank Research Observer*, The World Bank, Washington, DC.

Turvey, C. (1991), "Credit scoring for agricultural loans: a review with application", *Agricultural Finance Review*, Vol. 51, pp. 43-54.

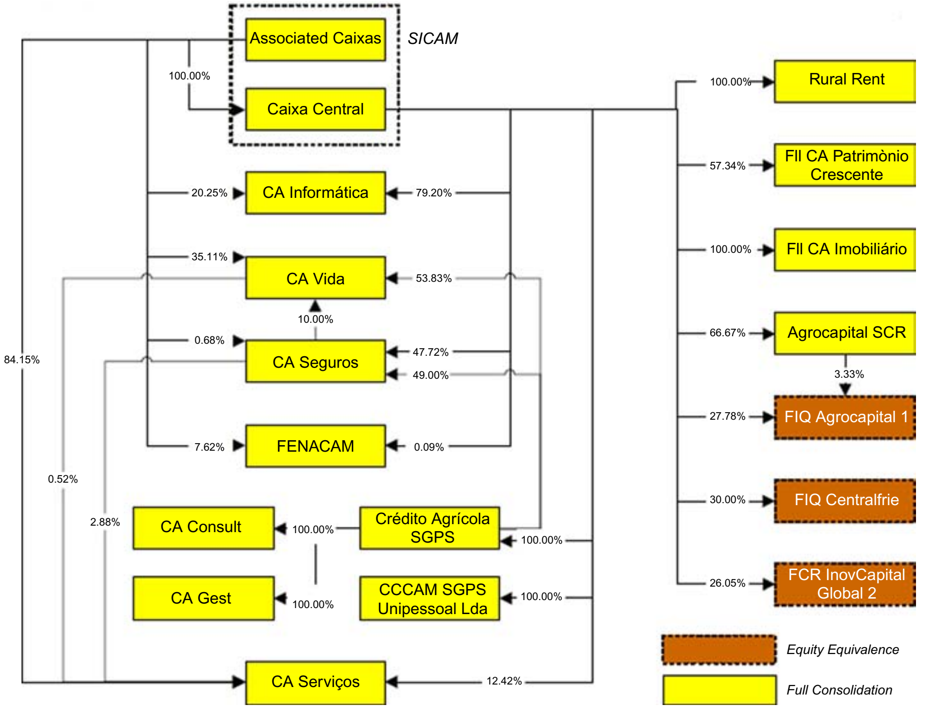
Turvey, C. and Weersink, A. (1997), "Credit risk and the demand for agricultural loans", *Canadian Journal of Agricultural Economics*, Vol. 4, pp. 201-17.

Wilcox, J. (2005), *Failures and Insurance Losses of Federally-insured Credit Unions: 1971-2004*, Filene Research Institute, Madison, WI.

Wilcox, J. (2010), *Determinants of Credit Union and Commercial Bank Failures: Similarities and Differences, 1981-2005*, Filene Research Institute, Madison, WI.

Zavgren, C. (1985), "Assessing the vulnerability to failure of American industrial firms: a logistic analysis", *Journal of Business Finance & Accounting*, Vol. 12, Spring, pp. 19-45.

Appendix



Notes: Credito Agrícola SGPS – holding company; CCCAM SGPS – holding company; CA Seguros – non-life insurance company; Rural Rent – long term car rental company; CA Servic¸os – shared purchasing and services company systems; CA Gest – funds and assets and liabilities management; CA Vida – life insurance company; CA Consult – mergers and acquisitions, consulting; CA Informática – data processing

Source: Crédito Agrícola (2010)

Figure A1.
SICAM and Crédito Agrícola Group structure

	Maximum	Median	Mean	Minimum	SD
Group 1 – solvent CCAM					
Credit Growth	3.1420	0.1003	0.1220	−0.2591	0.1558
Customers Resources Growth	3.6115	0.0855	0.1040	−0.4048	0.1319
Transformation Ratio	1.2989	0.6433	0.6388	0.1491	0.1535
Credit Overdue	0.3785	0.0592	0.0727	0.0000	0.0551
Intermediation Function Ratio	924.8692	2.9055	4.9202	−42.5351	27.5488
Labour Costs	1.0649	0.3242	0.3318	0.0663	0.1012
Structural Costs	1.9817	0.6082	0.6181	0.1881	0.1627
Expenses Ratio	1.7812	0.8432	0.7937	0.0000	0.2144
Liquidity	4.1073	0.3936	0.4686	0.0319	0.4246
Cash Flow	0.2338	0.0192	0.0232	−0.0046	0.0200
Indebtedness	0.9992	0.9012	0.8876	0.0565	0.0761
Debt to Equity Ratio	1,306.8825	9.1192	12.9563	0.0599	40.5262
ROA	0.2095	0.0121	0.0149	−0.1526	0.0171
ROSC	7.7375	0.1721	0.2600	−1.0915	0.4136
Financial Margin	0.3224	0.0368	0.0444	0.0011	0.0361
Total Assets[a]	352,466.001	31,205.577	44,072.790	726.085	44,008.339
Group 2 – insolvent CCAM					
Credit Growth	1.5464	0.0656	0.0786	−0.7422	0.1631
Customers Resources Growth	0.8374	0.0685	0.0748	−0.7874	0.0996
Transformation Ratio	1.0810	0.6254	0.6205	0.1226	0.1564
Credit Overdue	0.7254	0.1329	0.1674	0.0024	0.1274
Intermediation Function Ratio	419.1061	2.4129	7.2080	−63.2969	35.3760
Labour Costs	13.4681	0.3862	0.4270	−22.3365	1.3072
Structural Costs	23.6262	0.7420	0.8070	−33.5953	2.0992
Expenses Ratio	4.5101	0.9120	0.9514	0.0000	0.4784
Liquidity	5.0659	0.3978	0.5941	0.0360	0.6665
Cash Flow	0.8619	0.0156	0.0084	−1.0558	0.0826
Indebtedness	4.9566	0.9868	1.1140	0.4801	0.4977
Debt to Equity Ratio	19,147.8248	5.7891	45.6337	−314.8737	848.6963
ROA	0.8234	0.0070	−0.0079	−0.7060	0.0853
ROSC	9.3133	0.1443	−0.1928	−13.2999	1.9825
Financial Margin	0.5402	0.0344	0.0443	−0.3944	0.0581
Total Assets[a]	312,620.604	24,728.779	40,326.560	848.417	51,791.814

Note: [a]In thousands of Euros, 1995 prices

Table AI. Summary groups statistics

Corresponding author
João Rebelo can be contacted at: jrebelo@utad.pt