Forecasting insolvencies of Portuguese Co-operative Banks

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Abstract

This paper studies the insolvency risk factors of Portuguese co-operative banks. In general, little is known about the default risk of these institutions, since situations of financial distress are usually dealt with within their own organization. The objectives of the paper are twofold. Firstly, the paper aims at measuring the effect of bank specific financial indicators on the probability of failure of Portuguese co-operative banks. In order to do that, a default prediction model (logit) is estimated. The second purpose is to identify the risk factors determining the solvency conditions of the Portuguese co-operative banks. The estimation results suggest that risk indicators related to asset quality, management efficiency and dimension are significant predictors of failure among Portuguese co-operative banks. The analysis of the main risk factors of financial distress shows that the solvency conditions of Portuguese co-operative banks are, essentially, determined by the quality of credit portfolio, quality of management and also by local economic conditions.

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1 Introduction

The analysis of solvency conditions of co-operative banks is scarce, compared with the number of studies dedicated to commercial banks. However, the lack of empirical studies contrasts with the importance of co-operative banks as part of the banking systems worldwide. In 2010, 53 thousand credit unions had more than 187 millions members and they were located in 100 countries (World Council of Credit Unions 2011). Particularly in Europe, the co-operative banking sector has a large presence, comprising 181 million customers and 50 million members located in 27 European countries. Its total assets were 5.6 billion euros in the end of 2010, the deposits were 3.1 billion euros and the loans added up to 3.3 billion euros (European Association of Co-operative Banks 2011).

According to an empirical study by Hesse and Čihák (2007), co-operative banks are not only an important component of the financial systems, but they are also more stable than commercial banks. The authors also find weak evidence for a positive impact of a higher presence of co-operative banks on bank stability. In fact, given the non-profit maximisation characteristics of co-operative banks, they have lower incentives to engage in risky activities. However, as Fonteyne (2007) pointed out, co-operative banks face specific risks and challenges that can adversely affect not only their financial stability but also the stability of the banking sector as a whole. For instance, the co-operative banks might be more exposed to credit and interest rate risks, since the core business of their activity is still based on traditional intermediation, by capturing deposits and lending credit to costumers. As for challenges, Fonteyne (2007) highlights the governance model, based on a democratic decision-making process that should be adapted to deal with rapidly changing contexts in the financial systems. In addition, the co-operative banks face difficulties in managing their capital, due to the statutory or legal restrictions concerning membership and pay-out policies. In brief, the co-operative banks may be seen as generally stable, but authorities should be aware of the vulnerabilities that this group of banks face due to their co-operative nature. In particular, prudential authorities need to pay attention to these specifities when designing new rules for the banking system as a whole.

Having these issues into consideration, this paper aims to contribute to fill in the gap in the literature regarding the identification of the main risks affecting co-operative banks' financial stability, by i) forecasting the probability of default of individual Portuguese co-operative banks and by ii) identifying the main factors determining the solvency conditions of these institutions. For this purpose, it is used an unique dataset for Portuguese Agricultural Credit Co-operatives (hereinafter CCAM or Portuguese co-operative banks). This dataset comprises 148 Portuguese co-operative banks that have experienced serious solvency problems during the 1999-2006 period. In addition to financial indicators extracted directly from the Portuguese co-operative banks' balance sheets, this study also includes local economic indicators, such as GDP per region and unemployment rate per region, in order to assess whether local economic conditions have an impact on the solvency levels of Portuguese co-operative banks or on their probability of default.

The paper is organised as follows: literature about Early Warning Models and their application to commercial and co-operative banks is reviewed in section 2. Section 3 describes the insolvency cases among agricultural banks. The Early Warning Model used to forecast the insolvency risk is specified and estimated in Section 4. Section 5 presents the model to identify the main solvability factors of CCAM and the respective results. Section 6 concludes.

2 Forecasting co-operative banks' failures: a literature review

The research field concerning the study of the determinants of banking crisis and the development of early warning tools has received an increasing interest by scholars and central banks (see Sahajwala and Van der Bergh, 2000). Following the seminal paper of Altman (1968) that proposed the use of Early Warning Models (EWM) to the failure prediction of American firms, Meyer and Pifer (1970) and Sinkey (1975 and 1978) were the first to highlight the benefits of the employment of EWM in forecasting commercial banks' insolvencies. According to Sinkey (1975), the adoption of these methodologies by banking supervisors has important advantages, since it allows for a more efficient allocation of resources, once insolvent banks are identified. Moreover, it permits the introduction of objective criteria on the analysis of banking conditions, as a complement to on-site evaluations, that are generally more permeable to subjectivity. With the help of quantitative techniques, these models convert indicators of economic and financial performance into risk statistics that distinguish insolvent from healthy banks, thus giving a more efficient treatment of financial and economic information contained in the banks' balance sheets. Nonetheless, there is no doubt that the usefulness of EWM lies on its contribution to risk minimisation of systemic banking crisis.

After Meyer and Pifer (1970) and Sinkey (1975 and 1978), several studies suggested alternative methodology approaches. Three decades of subsequent intensive research produced different alternatives to the simple methods of the preliminary EWM, which may be divided in two different groups: Traditional Models and Artificial Intelligence Models. Traditional Models include Multivariate Discriminant Analysis (Sinkey, 1975), Logit (Thomson, 1991), Probit (Cole and Gunther, 1998) and Duration Analysis (Whalen, 1991; Dabos and Escudero, 2004). Artificial Intelligence Models include Trait Recognition Analysis (TRA) and Artificial Neural Networks (ANN), among others (see Kumar and Ravi, 2007).

However, the literature concerning forecasting of co-operative banks' insolvencies is scarce, compared with the studies devoted to commercial banks' insolvencies. Most of the literature about co-operative banks focus on issues related to efficiency or specific country cases (Hesse and Čihák 2007) rather than in financial stability aspects. As argued by Braga et al. (2006), who developed an Early Warning Model to signal forthcoming financial problems in the Brazilian credit unions, these institutions are currently dealing with the same type of risks that affect commercial banks. In this context, it is necessary to monitor their activity to identify high-risk credit co-operatives. Nevertheless, there are only two papers in the literature that are focused on forecasting probabilities of default of co-operative banks - Braga et al. (2006), for Brazilian co-operative banks and Porath (2004), for German credit co-operatives.

Braga et al. (2006) propose to adopt a Cox Proportional Hazards Model as an EWM to identify the credit unions that are more prone to financial problems. The study is based on data from 80 credit unions for the time period starting in December, 2001 to June, 2003. The results suggest that the most significant variables affecting credit union insolvency are general liquidity, salary and benefits expenses, and the loans to equity ratio. Porath (2004) estimated the probability of default for German savings banks and credit co-operatives using a discrete-time hazard model. This paper explored not only the effect of internal conditions on the probability of bank default but also validated the impact of macroeconomic information. They concluded that the most significant predictors of risk of default are capitalization, return, credit risk, market risk and the macroeconomic environment.

The inequality of treatment in the study of co-operative and commercial banks default factors can be related to the unavailability of information about insolvency events of co-operative banks. In some countries, such as Portugal and Germany, insolvencies among co-operative banks are solved discreetly inside their own system, through actions such as merger operations. Those actions prevent individual failure and, consequently, promote the stability of the banking system as a whole. However, by doing so, there remains no data available for researchers to undertake this type of studies.

3 The solvency problems of Portuguese co-operative banks

Caprio and Klingebiel (1997) defined three types of insolvencies. One type of insolvency refers to those events that are limited to a single bank or a small number of banks and are not systemic. The second type is related to overt banking system runs and results of panic reactions among bank debt holders. The third type is associated to financial distress and occurs when there is a large number of insolvent institutions, but the system as a whole remains in activity for an indefinite period. If, in some point in time, the public is uncertain about banks' economic health, the banking system can collapse as a consequence of overt bank runs.

The insolvency events taking place in the Portuguese Agricultural Mutual Credit Integrated System (SICAM) are characterized by insufficient coverage of liabilities by assets and, as pointed out by Cabo and Rebelo (2005), by difficulties in attracting capital. There are some CCAM with economic and financial problems but the system as a whole keeps functioning, and, in this sense, CCAM insolvencies may be identified as situations of financial distress in SICAM, i. e. the third type of insolvency according to Caprio and Klingebiel (1997) classification.

In the late 1980s and early 1990s, a number of insolvency situations were declared among Portuguese co-operative banks, prompting the implementation of an economic viability program in collaboration with the Mutual Agricultural Credit Guarantee Fund (thereafter the Fund),[1] as well as a reorganization plan that elected mergers as an essential tool to expand CCAM dimension and resolve insolvency problems. These programs were necessary due to the systemic effects that an individual failure could have on the destabilization of the entire SICAM. The financial assistance programs promote mergers between insolvent and sound agricultural credit co-operatives, geographically related, with financial support from the Fund .[2]

Since the Fund setting-up, in 1987, it has granted loans to 45 Portuguese co-operative banks in the total amount of 239.7 million euros (Fundo de Garantia do Crédito Agrícola Mútuo 2010). The merger processes put into action in this period had a large impact on the number of operating CCAM: from more than 200 CCAM in 1990, the number of CCAM was reduced to less than 100 in the end of 2010.

The SICAM, created in 1991[3], comprises the Central Mutual Agricultural Credit Bank and its co-operative banks. Along the history of Portuguese co-operative banks, the major characteristics of this group are associated to its traditional co-operative mission and to the closed relationship of its activity with the rural sector. According to Cabo and Rebelo (2005), the economic decline observed in this sector after Portugal has joined the European Union, in 1986, had an adverse impact on the profitability of the co-operative banks.

Nowadays[4], the SICAM is formed by 86 co-operative banks, which have 691 counters spread by the whole Portuguese territory, representing a 11,1% share of total number of counters in Portugal, and are holders of 400 thousand members and 1.2 million costumers. SICAM has a volume of deposits of about 10 billion euros and the loans were 8 billion euros in the end of 2010, which represented a share of 5.1% and 2.8% of total Portuguese banking system's deposits and loans, respectively (Crédito Agrícola 2010).

In this study, the sample comprises 148 CCAM, 18 of which were considered insolvent in the period between January 1, 1999 and December 31, 2006. The data was

[1]According to the Decree-Law No 345/98 of 9 November, the main tasks of the FGCAM are to guarantee the repayment of deposits with Caixa Central de Crédito Agrícola Mútuo (Central Mutual Agricultural Credit Bank) and with Caixas de Crédito Agrícola Mútuo (mutual agricultural credit banks) that are members of the SICAM (Integrated Mutual Agricultural Credit Scheme) and to promote and carry out the actions deemed necessary to ensure the liquidity and solvency of member banks.

[2]There are two different Deposit Insurance Funds in Portugal, the Fundo de Garantia de Depositos (Deposit Guarantee Fund) and the Fundo de Garantia do Crédito Agrícola Mútuo (Mutual Agricultural Credit Guarantee Fund). The former compensates depositors of authorised credit institutions, except Portuguese Agricultural Credit Co-operatives, which depositors are compensated by the Fundo de Garantia do Crédito Agrícola Mútuo (FGCAM).

[3]Although the current organisation model was created in 1991, its origins go back to the fifteenth century (1498). See a brief history of SICAM in www.creditoagricola.pt.

[4]The statistics presented are of December 31, 2010.

provided by the Central Bank of Portugal exclusively for this study[5] and is the quarterly information of the individual CCAM's balance sheets. The starting date of January 1, 1999 was determined by the availability of electronic data, while the ending date of December 31, 2006 was determined by the adoption, in the beggining of 2007, of new accouting rules (the International Accounting Standards) by Portuguese banking institutions.

Since there are no observable failures in the group of Portuguese co-operative banks, it is necessary to define a criterion to classify co-operative banks into solvent and insolvent categories. We define as an insolvent co-operative bank, one that having been incorporated by a financially stronger co-operative bank, had simultaneously benefited from financial assistance by the Fund. Having this definition of insolvency in mind, the annual number of insolvent CCAM along the time period considered in this analysis is showed in Table 3.1:

Table 3.1: Number of insolvent CCAM by year

Year	**No CCAM**
1999	2
2000	2
2001	5
2002	2
2003	0
2004	0
2005	4
2006	3
Total	**18**

4 Forecasting insolvency problems in Portuguese co-operative banks

4.1 Risk indicators and other explanatory variables

The risk indicators selected to forecast the solvency risk are those used in the empirical literature about bank failures and include the main variables considered in the CAMEL

[5]The Central Bank of Portugal supplied the individual accounting information without revealing the name of the co-operative institutions, classifying them with numbers, to assure confidentiality. The key to identify each CCAM was provided separately.

model, that is an acronym for: (C) Capital Adequacy, (A) Asset Quality, (M) Management Quality, (E) Earnings Performance and (L) Liquidity. The CAMEL model aims to capture the activity risks affecting financial institutions, that according to the Basel Committee on Banking Supervision (1997), are credit risk, country and transfer risks, market risk, interest rate risk, liquidity risk, operational risk, legal risk and reputation risk.[6] The measuring and comprehension of these risks are necessary to an effective banking supervision. Given the particular nature of Portuguese co-operative banks, that undertake traditional bank activities focused on the domestic market, the country, transfer and market risks do not have a significant impact in their activity.

Table 3.2 shows the risk indicators considered in this study:

Table 3.2: Risk Indicators

CAMEL Risk Dimensions	**Financial Indicators**
C - Capital Adequacy	Equity to Net Assets Ratio
A - Asset Quality	Total Credit to Total Net Assets
	Bad Loans to Total Credit
	Provisions for Bad Loans to Total Credit
M - Management Quality	Profit Margin to Gross Income Ratio
	Operating Costs to Gross Income Ratio
	Staff Costs to Gross Income Ratio
	(Operating Costs + Depreciation) to Gross Income Ratio
E - Earnings	ROA
L - Liquidity	Total Credit to Total Deposits
Size	Total Individual Net Assets to Total Net Assets of SICAM (annual average)

[6]The Basel Committee on Banking Supervision (1997) defines credit risk as “the failure of the counterparty to perform according to a contractual arrangement”. Country risk refers to “risks associated with the economic, social and political environments of the borrower’s home country”. Transfer risk is related to country risk and it occurs “when a borrower’s obligation is not denominated in the local currency”. Market risk is the risk that banks face related to “losses in on- and off-balance sheet positions arising from movements in market prices”. Interest rate risk is defined as “the exposure of a bank’s financial condition to adverse movements in interest rates”. Liquidity risk concerns “the inability of a bank to accommodate decreases in liabilities or to fund increases in assets”. Operational risks “involve breakdowns in internal controls and corporate governance”. Legal risk can take several forms: “laws may fail to resolve legal issues involving a bank”, “the risk that assets will turn out to be worth less or liabilities will turn out to be greater than expected because of inadequate or incorrect legal advice” or “laws affecting banks (...) may change”. Lastly, reputation risk refers to “operational failures, failure to comply with relevant laws and regulations”.

The banks make decisions about the level of equity to hold, because i) the risk of insolvency is declining in the capital structure, ii) the level of equity influences the return of stakeholders and iii) the supervision entities require a minimum level of capital (Mishkin, 2006). In this study, the capital adequacy is measured by one indicator: equity to assets ratio. A higher level of capital to assets ratio is positively associated with a lower risk of insolvency and, in contrast, a higher total credit to equity ratio may be related with a higher risk of insolvency. The Capital Adequacy Requirements to Risk Weighted Assets, used by supervision authorities to assess the solvability levels of banks, was not provided by the Central Bank of Portugal, even after request, in order to assure confidentiality.

Three proxies were considered to measure the asset quality with the aim of assessing asset management, which must observe three principles (Mishkin, 2006): profit maximisation, risk minimisation and guarantee of the liquidity of the bank. A high level of credit overdue to total credit ratio, used to measure the loans' probability of default, increases insolvency risk. The total credit as a percentage of net total assets is an indicator of asset diversification, with a higher value indicating lower diversification. The specific provisions against bad and doubtful debts may suggest that the bank has been a poor judge of credit risk in the past and this may continue in the future.

The quality of management is measured by four indicators. The Profit Margin to Gross Income Ratio assesses the level of dependence on traditional bank activity and a high value may suggest a higher insolvency risk. The remaining indicators reflect the efficiency of the bank and they are positively correlated with the insolvency probability. The Return on Assets (ROA) is a proxy for the bank's profitability and is negatively related to the risk of insolvency. The liquidity risk is captured by the proportion of total deposits applied in credit portfolio and it should be positively correlated with insolvency. An indicator of CCAM's dimension, measured by the individual CCAM's total net assets as a percentage of the average of SICAM's assets, was also included as an indicator of diversification opportunities and management sophistication.

Moreover, in this study we considered local economic indicators: the unemployment rate by region (NUTS II), the GDP by region (NUTS II) and the gross value added of agriculture by region (NUTS II).[7] All these variables were obtained from the Instituto Nacional de Estatística (Statistics Portugal).[8] These variables were included in the analysis with the purpose of inferring whether local economic conditions have an impact on the performance of co-operative banks. In particular, the gross value added of agriculture by region was considered to measure the impact of the agriculture sector on co-operative banks solvency indices, since their banking activity is traditionally associated to agricultural activities. Table 3.3 summarises the local economic indicators:

[7]NUTS II is a classification criterion of Portuguese regions. Following this criterion, the co-operative banks are located in 6 regions: Norte, Centro, Lisboa, Alentejo, Algarve and Acores.

[8]See Statistics Portugal website: www.ine.pt

Table 3.3: Local Economic Indicators

Unemployment rate by Region (NUTS II)
GDP by Region (NUTS II)
Agriculture Sector - Gross Value Added by Region

The descriptive statistics are shown in Appendix 1.

4.2 Methodology

The logit model is commonly applied in a wide range of empirical studies about bank failures as an Early Warning tool (see Thomson, 1991; Kolari et al., 2002; Jagtiani et al., 2003 and Lanine and Vennet, 2006). Logit is a parametric model and has the statistical property of not assuming multivariate normality among the independent variables, in contrast with Multiple Discriminant Analysis (MDA). The dependent variable is a dummy variable that, in bank failures forecasting exercises, assumes value 1 when the bank is classified as insolvent and 0, otherwise. Logit models have the advantage of allowing the measurement of the influence of each leading indicator in the probability of insolvency. In addition, the empirical results of past studies demonstrate its forecasting ability in what regards bank failures due to its reasonable level of precision. Nevertheless, as in any other parametric model, logit is not appropriate to exploring interactions between large numbers of variables due to losses in the degrees of freedom.

The Logit model is applied to cross-section data[9] and the determination of the cross-section time period depends on the merger date for insolvent co-operative banks.

In order to compare insolvent co-operative banks with solvent ones, it is necessary to have a control group of CCAM that have not experienced solvency problems in the past. Therefore, this group of CCAM comprises all the co-operative banks that do not fit the insolvency criterion. In this group, we can have two different situations: CCAM that were not involved in merger operations during the sample period and CCAM that were involved in merger operations as incorporating institutions. For the first subgroup, we selected December 31, 2002 as the time period to be considered in the sample (since it is a cross-section approach), because it is the middle point of our time series, that starts in March 31, 1999 and ends in December 31, 2006. For the second subgroup, the time period was determined attending to the consolidation process date: if it has occurred before December 31, 2002, it is considered the consolidation date; if afterwards, it is considered the December 31, 2002 period also for this group of CCAM.

To predict the probability of insolvency the following logit model was specified:

$$Log[P_i/(1-P_i)] = c + \lambda X_i + u_i \tag{1}$$

[9]Logistic regressions cannot be applied to panel data in our case, since the outcome (0 or 1) per co-operative bank does not change along the time span: a co-operative bank is considered insolvent or not.

where P_i is bank i default probability, c is a constant term, X_i are the explanatory variables, that comprise financial indicators and economic variables, and u_i is the error term.

Two different periods were considered in this analysis. The model was estimated using accounting and economic information for one (T-1) and two (T-2) years before the date of insolvency (T), which we assumed that corresponds to the date of the merger.[10] Then, we selected the observations for each indicator one and two years before the merger date. For solvent CCAM, the time period considered was December 31, 2002, as explained above. The estimation periods were selected to identify, *ex-ante*, the leading indicators of insolvency situations in SICAM and to obtaining models capable of maximising the ability to correctly predict the insolvency of CCAM.

Since the dataset has only a cross-section dimension, the size of each sample is relatively small: 97 observations for the T-1 full sample and 94 observations for the T-2 full sample. The remaining CCAM were excluded from the original sample due to one of two different reasons: i) because they were involved in merger operations without the Fund's financial support and, in these cases, it was not possible to be certain about their real financial situation, since the merger process might have been promoted due to strategic reasons or to deal with financially distressed co-operative banks,[11]or ii) they were merged in 1999 or 2000 and, given that we consider one and two years before the merger taking place, there is no availability of data for this group of CCAM since the sample period starts in 1999.

In addition, in forecasting analysis, it is useful to leave out of the sample some observations in order to evaluate the forecasting ability of the estimated model. We have opted to leave out roughly 10% (10 co-operative banks) of total sample for the periods T-1 and T-2, which makes up the hold out samples. The remaining observations, 87 and 84 for the T-1 and T-2 periods, respectively, are the in-samples, used to estimate the models.

Given the small dimension of the samples, we opted to perform an univariate analysis model as a first step, in order to evaluate the statistical significance of each individual indicator. After this analysis, we have selected only the indicators that revealed forecasting ability and we run the logit model for the T-1 and T-2 periods. As a final step, we tested the forecasting ability of both models based on the hold-out samples.

4.3 Estimation Results

This section presents the logit estimation results for T-1 and T-2 periods. The econometric software STATA 11 was used to obtain the estimation results.

[10]The date of the merger corresponds to the date of financial consolidation. This information was obtained from the Central Bank of Portugal's databases.

[11]These CCAM were analysed separately in order to distinguish insolvent CCAM from sound ones. However, this analysis was not conclusive, so we have decided to exclude them from the sample in order to avoid noise in the estimation process.

Table 4.2.1 shows the estimation results for one year (T-1) before the co-operative banks' failure:

Table 4.2.1: Logit Model - Estimation Results for T-1

Dependent Variable: Probability of Failure	**Logit Model**
Constant	-10.52*** (2.9582)
Bad Loans to Total Loans	34.5748** (14.6175)
Staff Costs to Gross Income Ratio	14.230*** (4.155)
Size	-1.8596* (0.9798)
Observations	87
Wald chi-squared (degrees of freedom)	14.40*** (3)
Pseudo R squared	0.78

* p < = .10; ** p < = .05; *** p < = .01

Robust standard errors are in brackets.

The estimation results suggest that the insolvency probability is determined negatively by the size of co-operative banks. Therefore, CCAM that have a higher dimension in terms of assets have associated a lower probability of failure. On the other hand, the proportion of bad loans in the credit portfolio (a measure of assets quality) and the percentage of staff costs in gross income (a measure of management quality) have a positive impact on the probability of failure, suggesting that an increase in each of these risk indicators will increase, *ceteris paribus*, the probability of failure of individual Portuguese co-operative banks. The local economic indicators were not statistically relevant to predict insolvencies one year ahead according to our results.

The analysis of bank insolvency prediction is based on two possible classification errors: predicting that the bank would not fail, when it did (type 1 error), or predicting that a bank would fail when it did not (type 2 error). The most important error to avoid is the type 1 error, because the scope of EWM is to minimise the number of real insolvencies by anticipating them. However, it is also useful to minimise the type 2 error, to avoid an inefficient allocation of resources, which means that it is important to achieve a balance between the two types of prediction errors. The hold-out sample results have, therefore, an important role in assessing the model's ability to predict insolvency problems. Table 4.2.2 shows the hold-out sample results for a randomly selected group of 10 co-operative banks left out of the in-sample for the purpose of checking the prediction ability of the estimated model.

Table 4.2.2: Hold-out sample prediction results in T-1

Observed	**Predicted**		**Total**
	0	**1**	
0	7	0	**7**
1	0	3	**3**
Total	**7**	**3**	**10**

The hold-out sample prediction results show a type 1 error of 0% (the 3 insolvent CCAM were correctly predicted by the model) and a type 2 error of 0% as well (all solvent CCAM were correctly predicted), which means that the model is able to forecast all the insolvency situations considered in the hold-out sample.

Table 4.2.2 shows the estimation results for two years (T-2) prior the co-operative bank failure:

Table 4.2.3: Logit Model - Estimation Results for T-2

Dependent Variable: Probability of Failure	**Logit Model**
Constant	-34.8209*** (11.2480)
Bad Loans to Total Loans	14.8188** (6.6864)
(Operating Costs + Depreciation) to Gross Income Ratio	25.4201*** (8.3160)
Total Credit to Total Net Assets	-28.3696** (12.6336)
Size	-5.9865* (3.1141)
Observations	84
Wald chi-squared (degrees of freedom)	25.22*** (4)
Pseudo R squared	0.83

* p < = .10; ** p < = .05; *** p < = .01

Robust standard errors are in brackets.

The coefficients' signs of all explanatory variables are as expected for the T-2 period estimation results. The total loans over total net assets, the proportion of credit overdue to total credit (quality of assets indicators) and the efficiency ratio (quality of management indicators), measured by the weight of the sum of operating costs and depreciation on gross income are accurate predictors of default of Portuguese co-operative banks. An increase of credit portfolio compared to overall net assets and of the proportion of non-performing loans in credit portfolio will have a positive effect on the probability of failure of these institutions, as well as a decrease in the efficiency measures.[12] At the same time, the estimation results show that size, measured by total individual net assets to total SICAM average net assets, has a negative and statistically significant impact on the probability of failure of Portuguese CCAM not only one year ahead, but also two years prior the default, suggesting that assets dimension of Portuguese co-operative banks is a critical variable to predict its financially assisted incorporation by another co-operative bank. Smaller co-operative banks will be more prone to failure than comparatively larger ones.

Once more, the results suggest that region economic performance is not a good predictor of the probability of Portuguese co-operative banks' insolvency.

Similarly, Table 4.2.4 shows the hold-out sample results for a randomly selected group of 10 co-operative banks, among which two were classified as insolvent.

Table 4.2.4: Hold-out sample prediction results in T-2

Observed	**Predicted**		**Total**
	0	**1**	
0	8	0	**8**
1	0	2	**2**
Total	**8**	**2**	**10**

The prediction results for T-2 in hold-out samples are as satisfactory as for T-1 period. The type 1 error is 0%, with the model being able to identify both cases of insolvency. As for the type 2 error, the model correctly identifies the 8 solvent co-operative banks in the hold-out sample. The model forecasting results in the hold-out sample suggest that it is possible to predict an insolvency among Portuguese co-operative banks two years ahead from the failure event.

However, there is an important caveat in this study, related to the small number of insolvent co-operative banks in the in-samples and hold-out samples. This occurs because the number of insolvent cases in the full sample is also small, only 18 in a total of 148 co-operative banks.

[12] An increase in the operating costs plus depreciation to gross income ratio corresponds to a decrease in the efficiency levels of these institutions.

5 Identifying solvency determinants of Portuguese co-operative banks

5.1 The Model

To better understand the inherent factors leading to insolvency problems in Portuguese co-operative banks we use a fixed effects model relating the solvency indicator, the capital to assets ratio, with the behaviour of the risk indicators and local economic variables previously described in Section 4. The dataset is the same presented in previous sections: it consists of a quarterly panel of 148 co-operative banks and the time period ranges from March 31, 1999 to December 31, 2006.

The model is the following:

$$Solvency_{i,t} = c + \sum \beta_i X_{i,t} + \varepsilon_{i,t},$$

$$\varepsilon_{i,t} = v_{i,t} + u_{i,t} \tag{2}$$

where $Solvency_{i,t}$ is given by the equity to assets ratio for co-operative bank i and period t, with $i = 1, 2, ..., N$ and $t = 1, 2, ...T$, c is a constant term, $X'_{i,t}s$ are the explanatory variables and $\varepsilon_{i,t}$ is the disturbance, with $v_{i,t}$ the co-operative bank specific effect and $u_{i,t}$ the idiosyncratic error.

For panel data, the estimation methodology selection must attend to some aspects related to unobserved heterogeneity (Wooldridge, 2002). Two methods for estimating panel data models have been suggested in the literature, namely fixed effects and random effects. These methods are distinguished by the assumptions about the unobserved effect behaviour. In the fixed effects model it is assumed that the unobserved effect is correlated with the regressors, whereas in the random effects model it is assumed that there is no correlation between this component and the explanatory variables. The results of Lagrange Multiplier[13] and Hausman Tests[14] supported the choice for the Fixed Effects Model. The robust covariance estimator was used in order to correct for autocorrelation problems that were detected in the model. The estimations were run by the econometric package Stata 11.

[13]The test compares the quality of fit of pooled OLS and fixed and random effects.

[14]The test compares the quality of fit of fixed effects and random effects.

5.2 Estimation Results

Table 5.1 presents the estimation results:

Table 5.1: Regression Results for Quarterly Panel Data 1999-2006

Dependent Variable: Equity to Assets Ratio	**Fixed Effects**
Incorporating CCAM	-0.0179** (0.0073)
Incorporated CCAM	-0.0432* (0.0247)
Bad Loans to Total Loans	-0.2617*** (0.0474)
Provisions for Bad Loans to Bad Loans Ratio	-0.0179*** (0.0057)
Loans to Assets Ratio	-0.8429*** (0.0957)
Operating Costs to Gross Income Ratio	-0.0423* (0.0235)
Profit Margin to Gross Income Ratio	0.0281* (0.0157)
Loans to Deposits Ratio	0.7017*** (0.0811)
Staff Costs to Gross Income Ratio	-0.0234 (0.0485)
Return on Assets (ROA)	0.0670 (0.1164)
Size	0.0117 (0.0188)
Unemployment Rate by Region	-0.1178* (0.0640)
GDP by region (log)	-0.00196 (0.0298)
Gross Value Added in Agriculture by Region	0.00003* (0.00002)
Time (quarters)	0.0012*** (0.0004)
Observations	4023
No CCAM	148
Log-Likelihood	44.03***
R squared	0.7620

* $p <= .10$; ** $p <= .05$; *** $p <= .01$

Robust standard errors are in brackets.

The estimation results indicates that the main factors determining solvency of CCAM are related to the quality of assets, quality of management, liquidity and local economic conditions, such as unemployment rate by region and the gross value added in agriculture by region. The participation of co-operative banks in mergers also affect negatively their solvency indices, despite of the co-operative bank is incorporated by or incorporating another co-operative bank. These results are as expected, since, for instance, the incorporating co-operative bank will merge with a less solvent co-operative bank, thus diminishing its own solvency ratios once the consolidation is completed. From the point of view of the incorporated co-operative bank, these institutions are chosen to participate in a consolidation process, because their capital ratios do not respect the adequate capital requirements established by the Central Bank of Portugal.

In addition, the results show that the size of a co-operative bank, GDP growth rate, return on assets and staff costs to gross income ratio are not statistically significant variables. Therefore, their impact on the co-operative banks' solvency ratios does not seem to be relevant.

In what regards the quality of assets component, the estimation results show that the percentage of bad loans in total loans, the percentage of bad loans provision in total bad loans and the proportion of loans in total assets are statistically significant at the 1% level of significance. The coefficients' signs are as expected: an increase in the value of each indicator has a negative impact on the equity to assets ratio. The importance of solvency factors associated to assets quality is argued by Porath (2004) and might be explained by the business model of co-operative banks, which is very dependent on banking traditional activities, particularly credit operations which can be concentrated in homogeneous groups and raise the credit risk.

Moreover, the quality of management is an important dimension of co-operative banks' balance sheet, mainly in what concerns to the proportion of operating costs in gross income, that has a statistically significant negative effect on solvency ratios, and the percentage of profit margin in gross income, that has a statistically significant positive impact on the equity to assets ratio. However, the staff expenses over gross income does not seem to be relevant to explain solvency patterns, which suggest that management skills are mostly important when it is at stake the management of operating costs not directly related to staff expenses.

Liquidity ratios are also important, according to our results. The proportion of deposits converted into credit has a positive impact on solvency ratios, which can be explained by higher indices of profitability of credit operations compared with other types of assets, such as cash or non tangible assets. As stated before, Portuguese co-operative banks are focused on the traditional banking activity, thus credit portfolio is the most important source of revenue of these institutions.

Finally, the local economic variables are also relevant determinants of co-operative banks' solvency ratios. The increase of unemployment rates in a certain region affects negatively the solvency ratios of co-operative banks. More interestingly, the gross value added in agriculture by region as a positive impact (although very small) in the solvency conditions of CCAM, which might suggest that co-operative banks' business model is still relying on these traditional economic sector. Therefore, given the specifities of Portuguese co-operative banks, such as their geographic circumscription, local conditions are relevant determinants of their performance, meaning that CCAM business is vulnerable to the economic performance of the regions where they are located.

In conclusion, the results suggest that the solvency conditions of Portuguese co-operative banks are, essentially, determined by the quality of credit portfolio, quality of management and some local economic conditions. When CCAM fail to adequately manage these two risk dimensions and to diverdify their business, the solvency conditions deteriorate, which may lead to an increase in the probability of insolvency.

6 Conclusion

This paper developed a model for the prediction of agricultural co-operative bank insolvencies in Portugal, a group of financial institutions that has a large incidence of solvency difficulties. We assumed that co-operative banks share the same risk factors as commercial banks, despite some specific characteristics of this type of institution, and used them to estimate an Early Warning Model of bank insolvencies. The main solvency factors of Portuguese co-operative banks were also identified in this study.

The estimation results for forecasting co-operative banks' insolvency suggest that risk indicators related to asset and management quality are the most relevant financial indicators of failure. Conversely, local economic conditions are not statistically significant indicators to explain the probability of default of these institutions, so they are not relevant for forecasting exercises.

The paper also studies the factors that determine solvency levels, with the regression analysis suggesting that CCAM with capacity to monitor and evaluate credit risk and to adequately manage their assets and liabilities will have stronger solvency levels. The study also unveils the importance of local economic conditions as determinants of the solvency ratios of Portuguese co-operative banks. These results are useful from the banking supervisors' perspective, since it presents early warning models to monitor and evaluate financial and economic conditions of these specific banks.

In further studies, it would be interesting to compare the forecasting performance of alternative capital adequacy ratios, such as the Capital Adequacy Requirements to Risk Weighted Assets, regularly used by supervision authorities.

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