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Full Length Research Paper

Developing a business failure prediction model for cooperatives: Results of an empirical study in Spain

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The use of statistical models to predict business failures has received considerable attention in recent decades. However, very few studies have been devoted to predicting failures of cooperative societies, which play an important social and economic role in many sectors and possess certain characteristics that distinguish them from investor-owner companies. This paper develops a statistical business failure prediction model specifically for cooperative societies and identifies the most powerful predictive variables. This is done by applying logistic regression to a sample of Spanish agricultural cooperatives with financial indicators as explanatory variables. The prediction models obtained, capable of predicting failures one or two years before they actually happen, reached an accuracy level of more than 94%. The best predictors confirmed the importance to cooperatives of having a minimum amount of capital available to ensure their financial independence, which could be put at risk by virtue of the cooperative principle of "voluntary and open membership", especially when financial problems appear on the horizon. The importance of the results-based indicators was also shown, which could be considered as obvious, given that the objectives of cooperative societies is to obtain the greatest possible advantage from the activities carried out for their members.

Key words: Business failure, cooperatives, financial indicators, logistic regression, predictive model.

INTRODUCTION

In recent years, the social and economic implications of business failures have been the subject of many studies that have aimed at developing prediction models able to foresee these situations and to make it possible to adopt the appropriate measures to avoid financial difficulties and also perhaps the disappearance of the company concerned. Company bankruptcies not only hinder economic and social development but also have disastrous effects on a wide variety of stakeholders (shareholders, workers, creditors, government bodies, clients and providers).

Since the pioneering work of Beaver (1966) and Altman (1968), many academics and professionals have been involved in developing and perfecting failure prediction models. Most of the empirical contributions have aimed to present the information contained in financial ratios as objective predictors of future solvency and have defined the variables that can affect this factor (Beaver, 1966; Courtis, 1978; Ohlson, 1980). The method normally used consisted of selecting a group of failed firms, and matching this group with another made up of non-failed firms with similar characteristics as to size and sector, analysing the economic and financial features that distinguish both groups and trying to identify the most suitable variables to use in foreseeing collapses. However, in spite of the large number of contributions, nobody has yet been able to formulate a theory of business failure or of the most important factors involved. Most studies have been limited to proving the worth of the information contained in financial or other variables as predictive elements.

Practically all the studies published have focused on business companies and have ignored the special distinguishing elements of other forms of business organization,

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including cooperative societies. Studies related to predicting failures in this type of enterprise are almost non-existent, a situation that is by no means justified, given their social and economic importance in certain sectors of activity. According to figures issued by the International Co-operative Alliance (ICA, 2011) the cooperative movement has over one billion members worldwide. In many countries, members form a significant percentage of the population (for example, 50% in Singapore, 40% in Canada and New Zealand, 38% in France, 33% in Iran, Japan and Uruguay, 25% in Germany, 20% in Kenya and 15% in Spain). Cooperative societies are almost certainly the largest commercial enterprises in the social economy and play important economic and social roles in the countries they operate in. They have an essentially private character, take independent decisions, are democratically organised and are active in the market, from which they obtain most of their income. They are present in the banking system and in practically all the other sectors of the economy. In Belgium, pharmaceutical cooperatives reach 19.5% of the market share; in Brazil, they produce more than 37% of the agricultural GDP; in Canada, cooperatives make 35% of the world's maple sugar; 30% of Cyprus banks belong to the cooperative movement; 99% of Norway's milk production and 75% of Poland's are in cooperative hands; Kenyan cooperatives are responsible for 45% of the country's GDP, 70% of its coffee, 76% of its milk and 95% of its cotton; 90% of French, Japanese and Korean farmers are members of cooperative societies. In Singapore, 55% of all the products sold in supermarket are bought by consumer cooperatives. In the UK, the country's largest independent travel agency is a cooperative. They also play an important role in creating and maintaining employment and provide over 100 million jobs worldwide or 20% more than the multinationals (ICA, 2011).

The cooperative movement is highly developed in Europe, with more than 123 million members and 160,000 cooperative organizations that employ 5.4 million people (Cooperatives Europe, 2010). Among members of the European Union (EU-27), Italy, Spain and France have the highest number of cooperatives, with France, Germany and Italy having the highest numbers of members. Most of the European cooperatives (42%) are in the industry and services sector, composed of many and diverse activities, with 33% in agriculture. The movement is important to the European agricultural sector, where it has greater influence than in other economic sectors and directly contributes to maintaining the level of agricultural incomes. In the EU-27 there are 38,000 agricultural cooperatives with 6 million members and a total turnover of € 360,000 000 (COGECA, 2010). More than 60% of European agricultural production is in the hands of cooperatives, and in some cases this is over 90% (milk production in Denmark, Austria, Finland and Holland). We should therefore, not forget the important contribution of cooperatives to the economic development of European rural areas, in which they provide a large number of jobs both directly and indirectly.

Cooperatives are different to other types of investor-ownerfirms and possess certain distinguishing features. This is due not only to the specific legislation (cooperative laws) to which they are subject, but also to their cooperative principles, which also differentiate them from other types of enterprise. From a practical point of view, the application of these principles involves not only their organization and management, but also their financial structure and social policies.

Studies into business failures have shown considerable evidence that prediction models are usually specific to the sample on which the empirical study has been carried out and consequently cannot be applied to general cases. Dimitras et al. (1996) maintain that even a good prediction model may not be successful in predicting the failure of different types of firms, which limits their value for other countries, sectors and time periods. Since the presence of cooperatives in relatively high numbers constitutes an important economic and social development tool in many areas, prediction models could be a valuable tool, not only to prevent failures, but also to help on developing specific financial assistance programs (Dietrich et al., 2005). Following in this line, and due to the social and economic roles of the cooperative movement within the framework of studies designed to construct a theory of business failures, the objectives of this paper are: 1) to design and validate a business failure predictive model specifically for cooperative societies and 2) to identify the indicators that can most effectively forecast their failure.

LITERATURE REVIEW

The first empirical studies on predicting business failures by means of financial ratios were based on univariate analysis, although this was soon replaced by a multivariate approach using multiple discriminant analysis (MDA). However, the validity of the results was called into question by the considerable statistical restrictions of this methodology (Eisenbeis, 1977; Ohlson, 1980). As a result, new methods appeared in the form of conditional probability models, of which the most important were the logit (Ohlson, 1980) and probit models (Zmijewski, 1984). More recent developments include the iterative participation technique, mathematical programming methods, multicriteria decision aid methodology (MCDA), artificial intelligence techniques, rough set theory (Pawlak, 1982; Dimitras et al., 1999) and genetic programming. Advances in computer and information sciences have contributed to the development of increasingly sophisticated and reliable models by overcoming the initial information processing limitations. At the present time, three different prediction models can be identified (Aziz and Dar, 2006): classical statistical models, artificially intelligent expert system models and theoretical models, although other authors classify the models into two general categories (Kumar and Ravi, 2007): statistical and intelligent techniques.

The classical statistical models can be said to possess certain limitations, some of which refer to the concept of business failure they use and consequently to their explanatory variables. Most of the models published in the academic literature are based on different statistical techniques and financial data from samples of failed and non-failed firms with the aim of predicting failures in a short-term time horizon, normally from one to three years before the failure (Cybinski, 2001). The models are based on the results of statistical study of financial indicators with the aim of empirically distinguishing healthy firms from those with problems. However, there does not appear to be a consensus on either the variables or on the best predictive models (Scott, 1981). Balcaen and Ooghe (2006) point out that most of the models based on multiple discriminant analysis or conditional probability are traditionally built on an arbitrary classification of the population of failed and non-failed firms. Indeed, the very definition of failure is in itself arbitrary and is a mixture of both legal and financial criteria. The term "business failure" normally refers to the suspension of business operations due to a continued inability to generate enough profits (Ahn et al., 2000). However, the variety of the situations in which such a firm could find itself means that researchers in the field must explicitly define their own concept of failure in the light of the aims of their study or of the nature of the data they use. The use of the legal concept of bankruptcy as a synonym of business failure (Deakin, 1972; Zmijwewski, 1984) entails specific problems, such as the fact that some firms use this legal mechanism as a strategic decision to solve their debt problems, or that bankruptcy may occur suddenly or accidentally (Hill et al., 1996; Davies and Huang, 2004), implying that in such cases, the firm will not give any previous warning of failure. According to Beaver (1966), the use of economic criteria itself implies a degree of arbitrariness in their definition, since a wide range of variables can be used without clarifying their relative importance.

The choice of the variables to be used in the model is directly influenced by the failure criterion adopted. In this respect there is relative consensus among researchers on the relevance of financial information, especially in those models that use an economic approach. However, some authors have criticized this restricted approach to the financial concept of failure, which appears to ignore its real dimensions, since not all the information relevant to a company's financial situation is reflected in its financial statements. The widespread use of accounting information in the form of financial ratios for predicting business failures is traditionally based on its objective and public (accessible) nature. Using financial ratios not only makes it possible to assess a company's financial situation and profitability, but also allows the strengths and weaknesses of different firms to be compared (Wu, 2010). The underlying hypothesis of financial ratios is that the financial statements provide a real and faithful picture of a firm's financial situation. However, it is reasonable to suppose that there may be certain companies whose financial statements cannot be relied on to reflect the real situation, especially when financial problems begin to be detected as the result of "creative" accounting, the lack of internal control (Keasey and Watson, 1987) or adjustments made by the auditors in the light of a declaration of bankruptcy.

For this reason, some authors (Ohlson, 1980; Keasey and Watson, 1987, among others), with the aim of giving a wider vision of business failures, point to the need to use non-financial qualitative information in prediction models, especially in the case of smaller companies whose accounts cannot be wholly relied on. In addition, financial indicators cannot be used to assess the extent to which owners of the business have achieved their intangible objectives (Jennings and Beaver, 1997), another obvious indicator of success or failure. This non-financial information could be composed of, for example, level of exports, the existence of important competitors in the same area, relations with financial institutions, level of diversification, industrial growth, market share, the characteristics of the board of directors, etc. (Balcaen and Ooghe, 2006).

RESEARCH METHODOLOGY AND DATA

The use and validity of business failure prediction models is no longer in any doubt, as has been shown by the many empirical contributions made in recent years. The idea underlying this research is that the special legal and organizational features of cooperative societies justify the development of a prediction model specifically for them, even though very few exist at the present time. By using a statistical model fed with financial indicators, the best predictors of cooperative failure are identified statistically and at the same time new evidence is collected for the construction of a theory on the subject. The methodology follows the usual procedure in the construction of failure prediction models, consisting of three steps: (Dimitras et al., 1996): sampling and data collection; method selection and specification of variables to develop a predictive model; and model validation. The perspective of the classic paradigm also requires the previous definition of the concept of failure that is to be used. In this case, it is associated with economic factors, that is, the company is bankrupt when its liabilities are greater than its assets.

Sample population

The study concentrated on Spanish agricultural cooperative societies, which at the present time numbers 3,989, with 1.16 million members and a total turnover of close to €19 billion (COGECA, 2010). As the model was to be fed with economic and financial data as variables, the sample of cooperatives was selected from the Iberian System of Balance Sheet Analysis (SABI), compiled by the Bureau Van Dijk Electronic Publishing e Informa, which collects financial information on more than 550,000 Spanish companies.

The criteria for the selection of failed cooperatives were the following: 1) type of business company: cooperative; 2) activity sector: all those related to agriculture, classified in accordance with the National Classification of Economic Activities (CNAE, 2009); 3) size: only cooperatives classed as small and medium enterprises (SME)[1] (Assets < € 2.8 million; turnover < € 5.7 million; number of employees < 50)[2]; 4) situation: cooperatives that were technically bankrupt were classified as failed; showing negative equity for two successive years (2006 and 2007); 5) availability of financial and economic information: the time horizon of the prediction model was for two years previous to failure, since it was considered that two years would have been sufficient time to establish and apply corrective measures to avoid the failure of the company. In this study, the year of failure was taken as 2007, so that information was needed for the years 2005, 2006 and 2007.

A total of 27 cooperatives were included in the sample of failed cooperatives that complied with all the mentioned criteria. The selection of the sample of non-failed cooperatives was carried out with the same criteria as before, with the exception of situation (4), which in this case was defined as firms with positive equity. The final selection of non-failed cooperatives was made by applying the statistical matching technique, so that each firm from the failed group was matched with another healthy cooperative from the same activity sector, of similar size and with similar availability of data. The total sample was composed of 54 cooperatives.

Selection of variables

The selection of variables for a prediction model is directly influenced by the failure criterion adopted (Hand, 2004), since this is modelled by a dependent variable or response, which is dichotomous, the two concurrency modes being whether the cooperatives were healthy or failed, according to whether or not they had gone into receivership. These two situations were coded as 0 and 1, respectively. On the other hand, the independent variables that could be used to explain the behaviour of the dependent variable were selected from the financial information contained in the cooperatives financial statements. The lack of an economics-based failure theory which could be used as the basis for the relationship between the variables and the occurrence of failure means that the selection of the independent variables is performed with the aid of statistical and econometric techniques using a set of commonly used financial ratios or indicators or those considered to be most significant in previous studies on business failures (Scott, 1981).

The bibliography contains a large number of financial indicators or ratios that have been used in previous empirical studies. From these, those that had been used in studies on SME were selected and adapted, due to the similarity with the types of cooperatives that made up the sample (Correa et al., 2003; Dietrich et al., 2005; Huang et al., 2008; Wu, 2010). A total of 52 financial ratios were selected for the study, classified into five categories: profitability, economic structure, financial structure, solvency and liquidity, participation rates in value-added and productivity (Table 1).

It should be emphasized that the ratios used to assess the profitability of a cooperative are substantially different from those used for investor-owner companies. Agricultural cooperatives often do not seek to maximise profits but basically try to maximize prices paid to their members for the products these supply to the cooperative. For this reason, the profitability of the members of an agricultural cooperative is normally calculated, not on accounting profits but on the difference between the price that the cooperative pays to its members and the normal market price. This means that estimating profitability requires the calculation of “corrected” net profits according to market criteria and not according to the prices paid to members (Gómez-Limón et al., 2003). This, of course, would be impossible to calculate from the financial statements and without the collaboration of the cooperatives themselves.

The values of the 52 financial indicators (except ratio 5, as explained earlier) for the three years included in the study (2005 to 2007) were calculated from the financial statements on the sample of cooperatives. Logistic regression (which is not subject to the normality restrictions that affect other methods, such as discriminant analysis and can also have categorical explanatory variables) and analysis of variance (ANOVA) techniques were then applied to the indicators. Statgraphics 5.1 for Windows software was used to process the statistical information.

In order to analyse the characteristics of the distributions of the financial indicators and the degree of fit with the normal distribution, a one-dimensional analysis was first performed on each of the ratios for the year 2005 (two years before failure). Analysis of variance was then applied to reduce the number of variables or ratios initially considered potentially able to explain the failure of cooperatives one or two years before they actually happened. Finally, the ratios obtained from the ANOVA were included as explanatory variables in the logistic regression to determine the probability of an observation (cooperative) belonging to a specific group (failed or non-failed) according to the behaviour of the independent variables (financial ratios).

RESULTS AND DISCUSSION

Conventional statistical methods of failure prediction have certain practical limitations due to restrictive assumptions such as linearity, normality and independence among predictor or input variables. The requirement for a normal distribution of these variables in certain statistical models means that their validity depends on taking a number of precautions to avoid as far as possible correlation problems, lack of proportionality between numerator and denominator and heteroscedasticity in the residuals of the regressions.

With the aim of analysing the distribution characteristics of the ratios employed and the degree of fit with the normal distribution, a one-dimensional analysis was therefore carried out on the values of the ratios defined as explanatory variables for the firms in the sample (N = 54) two years before failure occurred (2005). From the information thus obtained on the asymmetry and kurtosis coefficients (Table 2) together with additional information from boxplots, it was found that most of the ratios did not comply with the normality hypothesis, and only the ratios relating to economic structure showed a reasonable fit with the normal distribution. This evidence influenced the choice of the statistical techniques to be used in determining the best financial variables for forecasting business failures and ruled out the use of others such as discriminant analysis that did not comply with the initial

[1] Most Spanish agricultural cooperatives are included in the group of SME’s, which again confirms their importance in global business, since about 90% of all economic units in the world consist of SME’s (Campos-Garcia et al., 2011).

[2] The criterion used to determine whether a company belongs to the SME group is that established by Spanish legislation: Royal Decree 1515/2007 of 16 November, which approved the General Accounting Plan for Small and Medium Enterprises and specific accounting criteria for small enterprises (Art. 2).

Table 1. Financial ratios.

Profitability ratio		
R1	Operating profitability	Operating earnings/Operating total assets
R2	Operating margin	Operating earnings /Operating incomes
R3	Operating turnover	Operating incomes / Operating total assets
R4	Economic profitability	Earnings before interest and tax /Net total assets
R5	Financial profitability	(Earnings before tax + purchases from members)/Equity
R6	Borrowing costs	Interest expenses/total liabilities
R7	Contribution of asset to generated resources	Resources from pre-tax ops./Net total assets
R8	Contribution of non-current asset to generated resources	Resources from pre-tax ops./non-current assets
Economic structure ratios		
R9	Proportion of non-current Assets	Net non-current assets/Net total assets
R10	Proportion of current assets	Net current assets/Net total assets
R11	Proportion of tangible assets	Net tangible assets/Net total assets
R12	Proportion of intangible assets	Net intangible assets/Net total assets
R13	Proportion of financial assets	Financial assets / Net total assets
R14	Proportion of stock	Stock/ Net total assets
R15	Proportion of receivables	Receivables/ Net total assets
R16	Proportion of cash	Cash/ Net total assets
Financial structure ratio		
R17	Debt	Total liability/Equity
R18	Internal funding	Internal funds/Total assets
R19	External funding	External funds/ Total assets
R20	Equity	Equity/Total assets
R21	Importance of reserves	Reserves /Equity
R22	Liability	Total liabilities/ Total assets
R23	Non-current liabilities	Non-current liabilities/Total liabilities
R24	Current liabilities	Current liabilities/Total liabilities
R25	Long term capital	Long term capital/ Total assets
Solvency and liquidity ratio		
R26	Interest coverage	Profits before interest and tax/Finance costs
R27	Interest and current liability coverage	Profits before int. and tax/(Fin.costs+current liability)
R28	Capacity to return loans	Resources from pre-tax ops./ liabilities
R29	Capacity to return short-term loans	Resources from pre-tax ops./current liabilities
R30	Liquidity	Current assets/Current liabilities
R31	Acid Test	(Current assets-stock)/Current liabilities
R32	Cash	Cash/ Current liabilities
R33	Solvency	Net total assets/Liabilities
R34	Weight of working capital/Assets	(Current assets-current liabilities)/Total assets
R35	Weight of working capital/Equity	(Current assets-current liabilities)/Equity
R36	Coverage of non-current assets	Equity/Non-current assets
R37	Self-funding of non-current assets	Reserves/Non-current assets
Participation rates in value added and productivity		
R38	Importance of value added	Value Added /Operating incomes
R39	Amortisation/Value added	Amortisation expenses/Value added
R40	Personnel costs /Value added	Personnel costs/Value added
R41	Finance costs /Value added	Finance costs/Value added
R42	Taxes/Value added	Taxes/Value added

Table 1. Contd.

R43	Net profit /Value added	Net profit/Value added
R44	Total turnover	Operating incomes/Net total assets
R45	Non-current assets turnover	Operating incomes/Non-current assets
R46	Productivity of personnel	Operating incomes/Personnel costs
R47	Proportion of amortisation in operat. incomes	Operating incomes/Amortisation
R48	Tax rate	Tax/Profits before tax
Growth		
R49	Growth of assets	Variation rate of net total assets
R50	Growth of non-current assets	Variation rate of non-current assets
R51	Growth of operating incomes	Variation rate of operating incomes
R52	Growth of net profit	Variation rate of net profit

Source: Compiled by the authors.

conditions: that is, variance homoscedasticity between groups. The abnormality also invalidated the use of the mean as the distribution-characterizing parameter as well as the use of any multivariant statistical techniques based on it. It was therefore decided to opt for logistic regression (logit).

However, before carrying out the logit analysis, since the initial number of ratios necessarily produced information overlaps and multicolinearity, it became important to eliminate information that although valid added nothing or very little to the study. This was done by analysis of variance (ANOVA), which identifies significant differences between the values of a dependent variable according to different treatment levels or categories of the explanatory variable and also considers variability of the observations in each group. ANOVA was applied to the 52 variables in the initial list of variables for one and two years before failure. The financial variables selected from the two groups of cooperatives (failed and non-failed) were those with a significantly different mean that did not show signs of multicolinearity with the others (Ferrando and Blanco, 1998).

A second selection process was carried out on the ratios obtained from the ANOVA to determine the variables with a correlation coefficient of 0.63 or less with any of the others, one and two years, respectively, before failure. This was to ensure that any information repeated in two ratios was always less than 40% and thus avoided overlapping and multicolinearity, which was identified by observing values from the correlation matrix and its inverse, eliminating individually those most closely related to the others until multicolinearity among all the variables finally disappeared. In this way, the information contained in the original 52 variables was now contained in 7 and 10 variables for one and two years before failure, respectively (Table 3). These now made up the initial list of possible variables for the logistic regression. Other studies on the prediction of business failure also frequently use principal component analysis (PCA) to extract variables, which improves both the reliability and predictive capacity of the resulting model (Li and Sun, 2011; Shaw, 2003).

The results of this analysis revealed that the most significant variables in distinguishing failed cooperatives from non-failed ones showed certain stability with time and were indicators related to financial structure (R20: equity and R22: liability) and solvency and liquidity (through the capacity to return loans ratio (R28), cash (R32) and solvency (R33)). The profitability variable was also observed to be statistically significant, although its definition varied between the operating margin (R2) one year before failure and economic profitability (R4) two years before. These results showed the importance of capitalization policies in ensuring the survival of agricultural cooperatives; on one hand there was the predictive capacity shown by the composition of the financial structure (weight of equity, or, alternatively, external funds) and on the other, the static (cash and guarantee) and dynamic (capacity to return loans) solvency indicators. The immediate solvency and liquidity indicators (interest and current liability coverage (R27) and liquidity (R30)) disappeared as failure approached, even though these had proved to possess good predictive capacity two years before the failure.

The value added-productivity participation rates indicator relative to tax rate (R48) also showed a certain discriminating power and showed the importance of the tax advantages enjoyed by cooperatives under the Spanish tax system. However, it should be noted that this predictive power disappeared as the company approached failure (one year before). At the other extreme, none of the indicators relating to growth was significant and only an economic structure variable, relating to proportion of intangible assets (R12), was able to show a degree of predictive power.

Before applying ANOVA, the previous existence of the conditions necessary to validate the hypothesis must be confirmed: that is, the normality and homoscedasticity

Table 2. One-dimensional analysis.

Ratio	Statistic				
	Mean	**Variance**	**Standard deviation**	**Typified asymmetry**	**Typified Kurtosis**
R1	-1019.87	1.41E7	3759.30	-15.44	45.29
R2	-3380.63	2.70E8	16434.00	-20.57	73.36
R3	26174.40	1.07E10	103637.00	21.44	77.89
R4	-858.19	9.35E6	3057.90	-13.61	35.18
R6	185.35	31202.90	176.64	3.50	1.84
R7	-244.80	9.18E6	3030.15	-10.56	23.23
R8	1812.87	1.77E8	13310.2	21.93	80.42
R9	5020.59	6.35E6	2519.78	-0.85	-1.04
R10	4952.11	6.42E6	2533.49	0.90	-1.08
R11	4526.44	6.11E6	2471.48	-0.36	-0.93
R12	2422.76	8.47E6	2909.88	2.94	-0.36
R13	291.80	291133.00	539.57	6.98	7.98
R14	1361.89	2.43E6	1558.71	3.42	0.71
R15	2105.69	4.05E6	2011.36	4.42	3.06
R16	1288.54	3.11E6	1764.44	6.84	8.28
R17	-837456.00	4.17E13	6.46E6	-21.83	79.92
R18	-141.15	5.40E7	7347.91	-16.98	56.54
R19	1959.81	3.32E6	1821.41	3.61	1.20
R20	328.98	1.16E8	10777.90	-17.50	58.81
R21	9237.30	1.56E8	12507.80	7.77	11.59
R22	9655.76	1.16E8	10783.10	17.48	58.75
R23	2788.07	9.49E6	3079.92	2.44	-1.03
R24	7691.09	2.51E7	5007.82	10.08	29.83
R25	2895.61	8.42E7	9176.50	-15.54	49.27
R26	66858.70	1.07E12	1.04E6	14.79	47.19
R27	103.89	9.63E6	3102.88	1.85	6.71
R28	931.15	8.55E6	2923.82	4.07	6.87
R29	2323.76	5.60E7	7485.93	12.64	36.90
R30	16486.40	4.13E8	20329.20	6.66	7.29
R31	10574.30	2.18E8	14770.70	10.84	23.92
R32	4440.13	7.32E7	8552.86	10.28	18.96
R33	17942.20	3.62E8	19031.60	12.07	30.73
R34	6482.35	4.11E8	20282.80	6.69	7.35
R35	507655.00	1.62E13	4.02E6	21.86	80.09
R36	37654.00	6.74E10	259628.00	21.75	79.51
R37	16824.60	1.62E10	127130.00	21.32	77.37
R38	4324.28	2.67E8	16345.00	20.71	74.56
R39	1259.15	6.06E7	7786.60	-8.88	18.34
R40	2787.85	3.31E8	18195.00	-9.88	25.32
R41	350.33	1.15E7	3389.68	-10.71	24.61
R42	713.07	5.20E7	7212.57	10.32	43.24
R43	4889.59	6.00E8	24497.10	8.55	16.14
R44	22548.30	6.64E9	81484.40	21.13	76.23
R45	145317.00	2.71E11	520800.00	16.20	46.38
R46	151731.00	4.94E10	222219.00	7.76	9.24
R47	750889.00	3.34E12	1.83E6	13.42	34.87
R48	1452.09	2.30E6	1515.81	-1.40	-0.48
R49	702.61	1.61E7	4015.82	6.38	8.86
R50	884.70	4.24E7	6510.93	11.81	26.79

Table 2. Contd.

R51	-246.24	6.66E6	2580.30	1.29	0.80
R52	5.89E6	1.90E15	4.36E7	22.04	80.99

Source: Compiled by the authors.

(equal variance) of the dependent variables. This was duly done and although a number of financial ratios complied with these conditions, most of them did not comply with the normality hypothesis. However, this situation does not generally have a strong influence on validating ANOVA and the comparison of means, since the latter always have a distribution tending to normal, in accordance with the central limit theorem. The results obtained from validation tests are therefore, considered to be substantially valid, even for non-normal data, so that analysis of variance can be said to be a robust technique for deviations from normality. Also, the effect of unequal variance in the groups depends on the heterogeneity between the numbers of observations in each one. This means that it is possible to assume unequal variance when comparing means, provided that there is approximately the same number of observations in each group, as in this case. If, on the other hand, the number of observations in the groups were to be widely different, large differences in variance could have serious consequences (Peña, 2010).

In order to validate the factors that influence the probability of the cooperative going bankrupt, the variables that had passed the ANOVA selection were subjected to a logit forward selection analysis before being incorporated into the model. Of the 54 cooperatives that composed the sample, the failed organizations were assigned the code "0" and the non-failed were assigned a "1". For the models of one and two years previous to failure, the significance level of the assessment of the likelihood ratio was set at 0, so that the null hypothesis was rejected that is, it was accepted that the model was significant and it could be concluded, with a 99% confidence level, that at least one of the factors considered had an influence on the probability that a cooperative was going to end up bankrupt (Table 4).

The validity and effectiveness of the prediction models resulting from the empirical study were finally assessed by their degree of fit with the cooperative classification (failed and non-failed) (Kamath and He, 2006). Two types of classification error can be identified: Type I, which represent a credit risk (a failed company is classified as non-failed) and Type II, which could be classed as a business risk (a healthy company is classed as failed) (Ooghe and Spaenjers, 2010). Table 5 shows the prediction accuracy of the adjusted model by giving the percentages of Type I and II correct and incorrect predictions, which coincided for both one and two years previous to failure. The model was used to predict the response, using the information from each of the rows in the data sheets. If the predicted value was higher than the cut-off point, which was established at a failure probability of 50%, the response was predicted to be true, while if it was equal to or lower than the cut-off the response was predicted to be false. For all the 54 cooperatives analysed, for both one and two years before failure, the model made better predictions in the case of the failed companies than the healthy ones, reaching an overall prediction accuracy of 94.44%, which we consider satisfactory, given the limitations in the information on the financial statements of the cooperatives in the sample. The Type I errors represented 3.70% of the companies that failed both one and two years later, that is, the model classed two cooperatives from the failed group as healthy, when in fact they finally went bankrupt. A percentage (1.85%) of Type II errors occurred, that is, in only one case was a healthy firm wrongly classed as failed by the model[3].

The analysis of the results of the logistic regression (Table 6) for one year before failure revealed that the explanatory variables of the failed situation were operating margin (R2) and equity (R20), each of the estimated parameters ($ß_j$) being statistically different from zero. In fact, the chi-square with one degree of freedom presented a significance level that allowed the rejection, with an error less than 1%, of the null hypothesis that each of the coefficients was equal to zero. Both these variables contributed to increasing the probability that the cooperative would fail, since their estimated parameters presented a positive sign. With regard to the partial contribution of each factor to the model, an increase in the equity indicator was seen to cause the most significant increase in the probability that the cooperative would finally go bankrupt. However, two years before failure, the explanatory variables for failure were, in order, equity (R20), proportion of intangible assets (R12) and economic profitability (R4). The positive sign of the estimated coefficients of economic profitability and equity revealed that these indicators helped to increase the probability of failure. On the other hand, the negative sign of the estimated coefficient of proportion of intangible assets confirmed that this factor contributed negatively to increasing the probability of failure that is, the cooperatives with the largest weight of intangible assets over total net assets are least likely to find themselves bankrupt two years later. The results of column Exp($ß_j$) also revealed that the economic profitability and equity indicators produced the most significant increase in the probability of

[3] Both the Type I and Type II error percentages refer to the total number of cooperatives in the sample (non-failed and failed).

Table 3. ANOVA.

Period	Ratio		Sum of squares	Df.	Quadratic mean	F	Sig.
	R2	Inter groups	1.394E8	1	1.394E8	4.970	0.030
		Intra groups	1.458E9	52	2.805E7		
		Total	1.598E9	53			
	R20	Inter groups	1.653E9	1	1.653E9	6.120	0.017
		Intra groups	1.403E10	52	2.699E8		
		Total	1.569E10	53			
	R21	Inter groups	2.258E9	1	2.258E9	10.370	0.002
		Intra groups	1.133E10	52	2.179E8		
		Total	1.359E10	53			
	R22	Inter groups	1.654E9	1	1.654E9	6.130	0.017
One year before failure		Intra groups	1.404E10	52	2.699E8		
		Total	1.569E10	53			
	R28	Inter groups	8.282E7	1	8.282E7	8.390	0.006
		Intra groups	5.133E8	52	9.872E6		
		Total	5.962E8	53			
	R32	Inter groups	6.233E8	1	6.233E8	7.130	0.010
		Intra groups	4.545E9	52	8.740E7		
		Total	5.168E9	53			
	R33	Inter groups	6.188E9	1	6.188E9	13.370	0.001
		Intra groups	2.406E10	52	4.627E8		
		Total	3.025E10	53			
	R4	Inter groups	5.630E7	1	5.630E7	6.660	0.013
		Intra groups	4.393E8	52	8.448E6		
		Total	4.956E8	53			
	R12	Inter groups	2.426E8	1	2.426E8	61.170	0.000
		Intra groups	2.062E8	52	3.965E6		
		Total	4.488E8	53			
	R20	Inter groups	9.266E8	1	9.266E8	9.21	0.004
		Intra groups	5.230E9	52	1.006E8		
		Total	6.157E9	53			
Two years before failure	R22	Inter groups	9.239E8	1	9.239E8	9.17	0.004
		Intra groups	5.239E9	52	1.007E8		
		Total	6.163E9	53			
	R27	Inter groups	9.946E7	1	9.946E7	12.59	0.001
		Intra groups	4.108E8	52	7.900E6		
		Total	5.103E8	53			
	R28	Inter groups	1.389E8	1	1.389E8	22.99	0.000
		Intra groups	3.142E8	52	6.042E6		
		Total	4.531E8	53			
	R30	Inter groups	3.009E9	1	3.009E9	8.28	0.006

Table 3. Contd.

		Intra groups	1.889E10	52	3.634E8		
		Total	2.190E10	53			
	R32	Inter groups	5.021E8	1	5.021E8	7.74	0.008
		Intra groups	3.375E9	52	6.490E7		
		Total	3.877E9	53			
	R33	Inter groups	4.179E9	1	4.179E9	14.47	0.000
		Intra groups	1.502E10	52	2.888E8		
		Total	1.920E10	53			
	R48	Inter groups	1.780E7	1	1.780E7	8.90	0.004
		Intra groups	1.040E8	52	1.999E6		
		Total	1.218E8	53			

Source: Compiled by the authors.

Table 4. Global model performance.

Variable	One year before failure			Two years before failure		
	Sum of squares	**Df.**	**Sig.**	**Sum of squares**	**Df.**	**Sig.**
Model	62.6778	2	0.0000	65.2805	3	0.0000
Residual	12.1821	51	1.0000	9.57935	50	1.0000
Total (corr.)	74.8599	53		74.8599	53	
R^2		83.7268			87.2036	
R^2 adjusted for Df.		75.7119			76.5170	

Source: Compiled by the authors.

failure two years later.

Although none of the liquidity indicators appear as regression variables in any of the models, their values are significantly worse in the failed cooperatives, especially two years before failure. The mean value of the liquidity ratio (R30) is less than unity in the failed group, while it reaches a value close to 2.4 in the healthy group, which appears to indicate that immediate liquidity problems can also cause the failure of agricultural cooperatives.

These conclusions confirm the hypotheses already advocated in the research into cooperative management concerning the capitalisation problems experienced by this type of organization (Mateos-Ronco, 2008), most of which are seriously undercapitalised and thus often have an excessive burden of debt. The special characteristics of cooperative equity can often cause three problems: The cooperative principle of "voluntary and open membership" can involve fluctuations in their paid-up capital, which undoubtedly distinguishes them from investor-owner companies and is basically due to the constant changes in the number of members. The second factor is related to the traditional difficulty these organizations experience in gaining access to capital markets, since cooperative shares are not sufficiently attractive for acquisition by outsiders. The amount of their capital therefore depends on the contributions of their own members and the cooperatives' ability to generate resources via reserves. It should also be pointed out that cooperatives are required by law to create fairly high reserve funds and this burden falls on the shoulders of the members. In the present context of economic recession combined with a credit squeeze, the organisations that comprise the social economy are beginning to take actions both in Spain and other countries designed to improve their access to sources of capital by means of specific financial mechanisms. They are also aware of the need to extend these mechanisms to specific lines of current capital financing due to the need for extra financing at present experienced by a large number of cooperatives affected by serious liquidity problems.

Conclusions

In the framework of contributions to research on business

Table 5. Prediction accuracy of the model (one and two years before failure).

Variable	Accuracy (%)	Type I error (%)	Type II error (%)
Failed	96.30	7.41	-
Non-failed	92.59	-	3.70
Total	94.44	3.70	1.85

Source: Compiled by the authors.

Table 6. Results of logit analysis.

Variable	β_j	Standard error	Chi-square	Df.	Sig.	Exp(β_j)
Model for one year before failure						
R2 “Operating margin”	0.00064	0.00069	7.01938	1	0.0081	1.00064
R20 “Equity”	0.00217	0.00094	50.4468	1	0.0000	1.00218
Constant	-1.76819	1.03879				
Model for two years before failure						
R12 “Proportion of intangible assets”	-0.00210	0.00136	12.3251	1	0.0004	0.99790
R20 “Equity”	0.00374	0.00268	18.0337	1	0.0000	1.00374
R4 “Economic profitability”	0.00673	0.00468	8.4764	1	0.0036	1.00675
Constant	1.83037	1.90136				

Source: Compiled by the authors.

failure and due to the lack of a general theory and explanatory factors on the subject, this paper describes an empirical study whose aim was to create a specific prediction model for cooperative societies. The application of logit analysis provided prediction models with an accurate rate of over 94% in classifying cooperatives, a figure significantly higher than the average accuracy of other models designed to classify other types of enterprise, which is around 85% (Kamath and He, 2006). Additionally, the models obtained gave a low incidence of credit risk (Type I errors) and commercial risk (Type II errors).

The logit model’s optimal regressors identify the characteristics that identify the profile of the agricultural cooperatives that are likely to have to close down. Even though other researchers have pointed out that there does not always have to be a direct relationship between closed companies and financial difficulties (Headd, 2003), this does seem to be a constant element in the case of agricultural cooperatives. These organizations have long-term (under-capitalisation and excessive debts) and short-term (low liquidity) solvency problems, besides low activity levels that cause commercial problems in the form of low profits (low profit margins and results). The consequent inability to generate positive results leads to a continuous series of losses that eats into their capital and reserves. The healthy cooperatives, on the other hand, generally present a balanced financial structure and a higher level of activity that ensures higher profit margins and better business results. In addition, the predictive power of the proportion intangible assets indicator pointed out another basic problem of Spanish agricultural cooperatives: their small business size and the unnecessarily large installations for their levels of production. The societies with the lowest weight of intangible assets, or, alternatively, with the highest “tangible assets/total net assets” ratio present a higher probability of failure if their installations are under-used. The results obtained confirm the theory inherent in the management of agricultural cooperatives that emphasize the importance for their commercial development of maintaining a balanced financing policy and achieving operating turnovers that guarantee at least the minimum viable profitability.

Future lines of research will focus on two aspects; on one hand, the use of cooperative samples from different activity sectors in order to identify similarities and differences in the explanatory variables due to activity sector that could be responsible for cooperative failures. Another line will use non-financial criteria and variables to define failures in cooperative societies. In fact we are already working on the identification of these indicators through qualitative methodologies based on consulting experts in the field and in-depth interviews (Mateos-Ronco et al., 2011). However, the difficulty of access to this type of information constitutes a serious restriction since it will be necessary to consult individually each of the cooperatives in the study samples to obtain the data necessary for the statistical development of the model.

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REFERENCES

Ahn BS, Cho SS, Kim CY (2000).The integrated methodology of rough set theory and artificial neural network for business failure prediction. Expert Syst. Appl., 18(2): 65-74.

Altman EI (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. J. Financ., 23(4): 589-609.

Aziz MA, Dar HA (2006). Predicting corporate bankruptcy: Where we stand?. Corp. Gov., 6(1): 18-33.

Balcaen S, Ooghe H (2006). 35 years of studies on business failure: an overview of the classic statistical methodologies and their related problems. Br. Account. Rev., 38: 63-93.

Beaver WH (1966). Financial ratios as predictors of failure. Empirical research in Accounting: Selected Studies. J. Account. Res., 4(Supplement): 71-111.

Campos-Garcia RM, Garcia-Vidales MA, Gonzalez-Gomez O (2011). Relationship between cost and logistic practices in small and medium enterprises: A case study of Queretaro, Mexico. Afr. J. Bus. Manag., 5(4): 1245-1252.

COGECA (2010). Agricultural co-operatives in Europe. Main issues and trends. Available at: http://www.copa-cogeca.eu/Cogeca [Consultation date: 31/03/2011].

Cooperatives Europe (2010). European Co-operatives. Key Statistics. Available at: http://www.coopseurope.coop/spip.php?article828&var_recherche=st ati stics. [Consultation date: 1/04/2011].

Correa A, Acosta M, González A (2003). Business insolvency: an empirical analysis for SME’s. Revista Contab., 6(12): 47-79.

Courtis JK (1978). Modelling a financial ratios categoric framework. J. Bus. Financ. Account., 5(4): 371-386.

Cybinski P (2001). Description, Explanation, Prediction: the Evolution of Bankruptcy Studies? Manage. Financ., 27(4): 29-44.

Davies AHR, Huang X (2004). The stock performance of firms emerging from Chapter 11 and accidental bankruptcy. FMA Meeting, New Orleans (USA), 6-9. October.

Deakin E (1972). A discriminant analysis of predictors of business failure. J. Account. Res., 10(1): 167-179

Dietrich J, Arcelus FJ, Srinivasan G (2005). Predicting financial failure: some evidence from new Brunswick agricultural co-ops. Ann. Public Coop. Econ., 76(2): 179-194.

Dimitras AI, Zanakis SH, Zopounidis C (1996). A survey of business failures with an emphasis on prediction methods and industrial applications. Eur. J. Oper. Res., 90(3): 487-513.

Dimitras AI, Slowinski R, Susmaga R, Zopounidis C (1999). Business failures prediction using rough sets. Eur. J. Oper. Res., 114: 263-280.

Eisenbeis RA (1977). Pitfalls in the application of discriminant analysis in business, finance, and economics. J. Financ., 32(3): 875-900.

Ferrando M, Blanco F (1998). Prediction of business failure in Valencian Region (Spain): application of discriminant analysis and logit models. Span. J. Financ. Account., 95: 499-540.

Gómez-Limón JA, Casquet E, Atance I (2003). A financial analysis of agrarian co-operatives in Castille and León (Spain). CIRIEC-Spain Rev. Public Soc. Coop. Econ., 46: 151-189.

Hand DJ (2004). Marginal classifier improvement and reality. Symposium on Data Mining, Ghent University (Belgium), May.

Headd B (2003). Redefining Business Success: Distinguishing Between Closure and Failure. Small Bus. Econ., 21: 51-61.

Hill NT, Perry SE, Andes S (1996). Evaluating firms in financial distress: an event history analysis. J. Appl. Bus. Res., 12(3): 60-71.

Huang SH, Tsai CF, Yen DC, Cheng YL (2008). A hybrid financial analysis model for business failure prediction. Expert Syst. Appl., 35(3): 1034-1040.

International Co-operative Alliance ICA (2011). Statistical Information on the Co-operative Movement. Available at: http://www.ica.coop/coop/statistics.html. [Consultation date: 31/03/2011].

Jennings P, Beaver G (1997). The performance and competitive advantage of small firms: a management perspective. Int. Small Bus. J., 15: 63-75.

Kamath R, He Y (2006). Business failure prediction in the retail industry: An empirical evaluation of generic prediction models. Acad. Account. Stud. J., 10(2): 97-110.

Keasey K, Watson R (1987). Non-financial symptoms and the prediction of small company failure: a test of Argenti´s hypotheses. J. Bus. Financ. Account., 14(3): 335-354.

Kumar PR, Ravi V (2007). Bankruptcy prediction in banks and firms via statistical and intelligent techniques – A review. Eur. J. Oper. Res., 180(1): 1-28.

Li H, Sun J (2011). Empirical research of hybridizing principal component analysis with multivariate discriminant analysis and logistic regression for business failure prediction. Expert Syst. Appl., 38: 6244-6253.

Mateos-Ronco A (2008). The bankruptcy proceedings in cooperative societies. Specifically on the financial resources. CIRIEC-Spain Rev. Public Soc. Cooperative Econ., 60: 209 – 246.

Mateos-Ronco A, Marín M, Marí S, Seguí E (2011). Business failure prediction models in agricultural cooperatives. CIRIEC-Spain Rev. Public Soc. Cooperative Econ., 70: 179-208.

Ohlson J (1980). Financial ratios and the probabilistic prediction of bankruptcy. J. Account. Res., 18(1): 109-131.

Ooghe H, Spaenjers C (2010). A note on performance measures for business failure prediction models. Appl. Econ. Lett., 17: 67-70.

Pawlak Z (1982). Rough sets. Int. J. Inf. Comput. Sci., 11: 341-356.

Peña D (2010). Regression and experiment design. Alianza Ed., Madrid, Spain.

Scott J (1981). The probability of bankruptcy: a comparison of empirical predictions and theoretical models. J. Bank Financ., 5(3): 317-344.

Shaw P (2003). Multivariate statistics for the environmental sciences. Hodder-Arnold.

Wu WW (2010). Beyond business failure prediction. Expert Syst. Appl., 37: 2371-2376.

Zmijewski ME (1984). Methodological issues related to the estimation of financial distress prediction models. J. Account. Res., 22(Suppl.): 59-86.