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Credit Risk Analysis: Reflections on the Use of the Logit Model

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Abstract

The present economic and financial crisis has underlined the importance to financial institutions and investors of having access to efficient methods of quantifying credit risk, or the probability of default. The logit models are among the techniques commonly used by large organizations and rating agencies for predicting insolvency. However, it should be borne in mind that some problems arise when using these models, such as the selection of the explanatory variables or the composition of the sample from which the model is obtained. These aspects have a decisive influence on the prediction models used to quantify companies' credit risk. The present study describes the problems that arise with logit on a sample of Spanish companies and shows that the estimated prediction models are indeed modified by changes in the sample on which they are based.

JEL classification numbers: G22, D81
Keywords: Credit risk, Default, Logit Model

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1 Introduction

The study of the probability of default and the creation of credit ratings existed even before 1909, when Moody's, Fitch and Standard & Poor started to analyse the situation of US railway companies. However, the origin of this line of investigation is attributed to Beaver and Altman at the end of the nineteen sixties. Using univariate analysis on 30 different ratios, Beaver [1] showed that the value of certain ratios varied significantly between healthy companies and those in financial difficulties. Altman [2] later used linear discriminant analysis on various financial ratios in a multivariant context to develop insolvency prediction models. This study encouraged other researchers to look for new statistical and econometric techniques that would provide a method of predicting defaults, including the famous Z-score created by de Altman et al. [3]. Without being exhaustive, among the pioneering papers we can include: Jensen [4], Gupta & Huefner [5], who used cluster analysis; Vranas [6] with a linear probability model; the work of Martin [7], Ohlson [8], Zavgren [9], Peel [10], Keasey et al. [11] and Westgaard & Wijst [12] on logit models; Zmijewski [13], Casey et al. [14] and Skogsvik [15] with probit models; Luoma & Laitinen's study [16] based on survival analysis and the work of Scapens et al. [17] on catastrophe theory. In the last two decades, researchers have focused on artificial intelligence and non-parametric methods, including: mathematical programming, expert systems (Elmer y Borowski, [18]; Messier & Hansen, [19]), machine learning (Frydman et al., [20]), rough sets (Slowinski y Zopounidis, [21]; Dimitras et al., [22], McKee [23], neural networks (Wilson & Sharda, [24]; Boritz & Kennedy, [25]) and multicriteria decision analysis – MCDA (Andenmatten, [26]; Dimitras et al., [27]; Zopounidis & Doumpos, [28]). In many of these studies a high degree of precision was achieved in classifying and predicting business defaults.

It should be pointed out that although there are many methods of estimating the probability of a default, as stated above, at the present time the traditional methods, especially those based on the logit model, are still preferred by professionals in the field. In fact, they are the principal tool of the rating agencies and are often used as a benchmark in academic studies to quantify credit risks. However, one must be aware of certain robustness problems that can arise when using logit, especially in relation to the composition of the sample used to estimate the model. By this we do not mean that the use of logit models should be abandoned, but rather that researchers should pay close attention to three factors: the choice of variables to be used in the model, the influence of the sample on the model results and the cutoff point. Financial variables, especially accounting ratios, are normally used in this type of works and it is not usually advisable to mix absolute and relative variables. Since a choice can be made from a wide range of variables, a factor analysis is normally carried out to reduce their number, keep the degrees of freedom high and avoid multicollinearity problems, while ensuring that the principal financial dimensions (profitability, liquidity, solvency, etc.) are represented. Evidently, it is highly probable that the result of the factor analysis will be influenced by the sample of companies used; if these companies are changed, the variables selected after the factor analysis will also vary.

Whatever the variables used, the logit model finally obtained will depend on the sample on which the model is based. This means that only some of the preselected variables will actually be used in the model, since both the selection and the weighting of the variables will depend on the sample of companies.

Also to be taken into account is the fact that whatever cutoff point is chosen, even though it will not modify neither the selected variables nor their weights, this cutoff point will affect the discrimination process and thus also the percentage of correct and incorrect predictions.

In the present study we will use the logit model to analyse credit risk on a sample of Spanish companies using financial information. Throughout the model estimation process we will see how the estimated models will in fact vary as the sample is modified. This point is of great importance for researchers and professionals, since it shows the high degree of dependence of the models on the sample used. A fundamental part of the process is therefore to ensure that the sample is appropriate to the case.

The rest of the paper is structured as follows: the following section describes the data base of the companies used in the study. Section 3 deals with the selection of the independent variables. Section 4 describes the estimation of the logit model from different subsamples and how changes in the sample influence the models obtained. Finally, the main conclusions reached are presented in Section 5.

2 Description of the Data Base

The preliminary phase of the application of a statistical analysis focuses on identifying companies considered to be experiencing problems, or indications of companies in trouble. When using legal and financial information of the companies, there is no unique definition of which business situations should be taken as evidence of failing businesses; the most generally accepted is that of being involved in bankruptcy proceedings. Apart from the legal definition, there are other types of financial information that can be taken into account, such as technical bankruptcy, net negative worth or operating losses for two or more consecutive financial years.

The present study considers both the legal situation (being su8bject to court proceedings) and net negative worth (technical bankruptcy) when classifying the financial situation of the companies in the sample.

The data base for our study consisted of Spanish companies with total assets between €2m and €50m in 2007, and information for financial year 2007 was obtained for them from the SABI data base.5 The firms belonged to Group A (agriculture, stock-farming and forestry), Group C (manufacturing, food processing and soft drinks) as classified by the National Classification of Economic Activities (CNAE, 2009).

A total of 49 companies from the sample were considered to be insolvent (Table 1 in the Appendix) as defined above.

The financial information of the companies was then analysed and a comparison was made between the solvent and insolvent firms. This information is summed up in Table 2 (in Appendix), which gives the mean values of their main assets and liabilities.

From this information certain differences can be detected between healthy companies and those in difficulties as regards the process that sets active companies on the road to bankruptcy. The most striking aspect is that the firms experiencing default have very high ratios of both short and long term debts; the short-term are two and a half times greater than equity and the long term are even higher. This is clear evidence of financial

[5] Publisher of the SABI data base (*Sistema de Análisis de Balances Ibéricos*): Bureau van Dijk

difficulties and shows that part of the short term debt has been converted to long term in an effort to avoid collapse.

An analysis of the ratio between equity and assets for both types shows that while solvent firms reach almost 50% of total assets, the insolvent only reach 1%, an indication of their difficult situation. It seems reasonable that over a number of years the bankruptcy process would involve capital being reduced to such an extent that it often reaches negative values.

3 Selection of the Independent Variables

A set of long-established financial and accounting ratios were selected from the firms' balance sheets as independent variables, chosen both for their ease of computation and for having been frequently used in previous studies.

The list, belonging to different categories such as liquidity, solvency, profitability and economic structure, is given in Table 3 (see in the Appendix).

When working with a list of interrelated ratios, most studies that apply a regression model, as in the logit case, carry out a preliminary step using principal component factor analysis or similar techniques to reduce the number of variables and avoid statistical problems, such as multicollinearity. In this way the observable variables (the calculated ratios) are grouped into a set of non-observable variables or non-correlated factors. So the variables assigned to a factor will be closely related to each other but not to the variables assigned to other factors.

The Kaiser criterion was used in the application of the principal components analysis to the data base of the firms. This consists of selecting components with an eigenvalue higher than 1, i.e. with greater explanatory capacity than the average single factor. Nine components were extracted with a cumulative percentage of explained variance of 78.50%.

Table 4 in the Appendix gives the varimax orthogonal rotation of the factor matrix to facilitate the interpretation of the non-correlated factors so as to achieve a better assignation of the variables.

Each variable is assigned a single factor, the one that presents the highest factor weighting, as shown in Table 5 (see in the Appendix).

As can be seen, certain groups of variables are closely related to each other and thus were grouped into their corresponding factors. For example, Factor 1 groups the variables related with profitability and earnings. Factor 2 is related to cash, 3 to productivity, 4 to covering financial expenses and 7 to liquidity.

The logistic regression model is formulated after assigning the different variables to the appropriate factors. The dependent variable is solvency or default and the independent variables are selected by a method that combines stepwise variable selection according to the Wald variable selection algorithm with the criterion of choosing a single variable from each factor.

4 Applying the Logit Model to the Prediction of Business Failures

Given a dichotomous dependent variable, logistic regression constructs a predictive model that will forecast the group to which an observation belongs using one or more independent variables. Like the ratios described above, in this case the independent variables are quantitative. In other words, the logit technique provides a linear combination of independent variables (financial ratios) that makes it possible to estimate the likelihood of a firm belonging to either of two previously defined sub-populations or groups (the dependent variable in this case will be default and will take the value 0 if the firm has been defined as solvent, while it will take the value 1 if the firm has been defined to be in default). Each firm can only belong to one group. The model calculates the probability "p" of the firm belonging to the second (insolvent) subpopulation by expression (1):

$$p=\frac{1}{1+e^{-\left(\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_k X_k\right)}} \tag{1}$$

Xi being the independent variables (ratios) included in the model and β the estimated coefficients for each of the ratios used. If this probability is equal to or greater than 0.5, the firm is classified as belonging to this subpopulation, and if not, it is placed in the first group (defaulted companies). In the samples used in the present study the independent variables for the model were selected from the factors obtained from the factor analysis shown in Table 6 (in the Appendix):

To obtain the prediction model for the firms' future financial state, different analyses were carried out by logistic regression, firstly for the initial sample of firms and then for different subsamples within the set of initial companies. The model results are given below for each case. Later they are analysed and interpreted. When the model was being constructed, due to the fact that around 8% of the firms in the original sample were insolvent (49 out of 622), different initial probabilities of belonging to one group or the other and different cutoff points were considered.

The Forward method (a new variable is introduced in each step) and the Wald statistic were used in all the models to select the subset of variables to be included.

Table 7 gives the model estimated by logit regression for the sample of 622 firms from the Spanish food and agriculture sector using financial information as of 2007.

As can be seen on Table 7 in the Appendix, the calculation was repeated, changing only the cutoff point from 0.5 to 0.2. In this case, when the model assigns a value greater than 0.2 the firm is classified as insolvent. Another result to be borne in mind is that the probability of being in the first group (non insolvent firms) is reduced, but on the other hand the probability of correctly predicting insolvency is increased.

The analysis was then repeated again, dividing the sample into two groups at random. These results are shown in Tables 8 and 9 (see in the Appendix).

For the first half of the sample in Table 8, the percentage of correct predictions has improved in both the 50% (from global 95.30% to 97.10%) and 20% cutoff points (91.20% to 92.90%). However, in the second half prediction accuracy in the overall classifications was slightly worse at the first cutoff point (0.5) and improved slightly at the second (0.2). The percentage of correct classifications was reduced in the group of insolvent firms in the second half.

Finally, the third balanced sample (subsample), dealing with an equal number of insolvent and non-insolvent firms, gave the results for a 0.5 cutoff point as shown in Table 10 in the Appendix. Both the overall and group classifications have improved, reaching 97.60% in all cases.

It can also be inferred from Tables 7-10 that the coefficients of the variables are significant in all the samples except in the last, in which, even though it has two variables, only the one representing equity over total assets is significant, at 90% (0.1). We can also see that most of the beta coefficients have negative signs except when the DPC variable appears (cash and realizable assets over short-term debts). It should be noted that this is caused because the insolvent firms are assigned to the second group (giving them a value of 1 and healthy firms a value of 0). If the coding of the dichotomous variable were to be modified, with insolvent firms in the first group (0) and solvent in the second (1), the signs of the coefficients would change, but not their values.

Exp (β) indicates whether or not a variable influences the probability of default. In the variables in which this value is higher than 1, the influence is in proportion to the value; if the values are less than 1, the influence on the result is reduced.

The only variable present in all the models is the ratio of equity over assets, perhaps because the firms classified as technically bankrupt were included in the insolvent group, even if their legal situation had not been modified. In second place is short-term debt coverage over disposable and realizable assets.

5 Conclusion

There is no doubt about the critical importance, especially for the financial sector, of identifying and managing credit risk. A large number of models have been developed in recent decades that use financial data to differentiate between healthy and troubled companies, of which those based on logistic regression are among the most widely used by rating agencies, financial organizations and academic researchers. In spite of the fact that this model is unquestionably useful and is even taken as a benchmark to measure the performance of new methods, it is not completely free of difficulties, such as the selection of the appropriate sample to estimate the model. This question should be borne in mind by researchers and those active in the professional field, who very often do not give it the attention it deserves.

The present paper describes the credit risk analysis of a number of Spanish business companies by means of the logit model. An analysis is made of the causal relationship between a classification variable and different independent variables based on information from the firms' balance sheets, with the aim of predicting their classification into solvent and insolvent firms 12 months in the future. After carrying out a factor analysis to select the explanatory variables, various logit models were estimated by Wald's forward method on four different samples of business companies. The first sample contained the entire population of selected companies, the second only 50% of the total number selected at random, the third contained the remaining 50% and the fourth a balanced sample made up of one half insolvent and one half solvent companies. Since the same logit model was estimated by Wald's forward method but on different samples, we were able to show how the variables that finally appear in the models had undergone changes, as did the weighting of each one, and how the predictive ability was also modified as the sample or cutoff point varied. The best prediction results were obtained from the final sample, which was the smallest and also the most balanced.

The main conclusion that can be drawn from this work is the importance of the influence on the models of the sample from which the estimations are obtained. The selected database may have a big impact on the models obtained to calculate the probability of default. Indeed, together with the problems mentioned in this paper, there are other

important problems the researcher must face, as the quality and reliability of the data, the fact that financial data for most companies are only published once a year and regarding a situation which occurred several months ago, and the survival bias.
All this aspect is important due to the large number of studies that make use of these models and the importance in the present economic situation, especially to financial organizations and investors, of being able to distinguish between financially healthy companies and those in distress.

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Appendix

Table 1: Causes for the insolvency of companies included in the sample

	Subject to court proceedings	Net negative worth
Number of insolvent companies	22	27

Table 2: Mean values of main assets and liabilities of firms included in the sample

	Solvent firms (€)	Insolvent firms (€)
Total assets	18 530 112.00	20 514 654.57
Current assets	9 555 091.30	7 738 751.14
Non-current assets	8 975 020.70	12 775 903.43
Current assets / Total assets	0.52	0.38
Fixed assets / Total assets	0.48	0.62
Equity	8 186 022.40	-236 171.53
Current liabilities	6 918 850.83	8 747 684.69
Fixed liabilities	3 425 238.77	12 003 141.41
Current liabilities / Equity + Liabilities	0.37	0.43
Non-current assets / Equity + Liabilities	0.18	0.59
Equity / Equity + Liabilities	0.45	-0.02

Table 3: Ratios used in the empirical analysis

ROA	Operating income / Total assets
RAI	Pre-tax profits / Total assets
RE	Ordinary profits / Total assets
RRF	Financial results / Total assets
REV	Ordinary results / Sales
AU	Equity /Creditors
C1	Total assets / Creditors
C2	Assets / Creditors – Cash – Temporary investments)
L1	Cash / Short term creditors
L2	Cash / Assets
L3	Current assets / Short term creditors
L4	Operating income / Current liabilities
L5	Creditors / Short term creditors
ROAGF	Operating income / Financial expenses
FA	Sales / Total assets
P1	Operating income / Sales
P2	Sales / Personnel expenses
P3	Sales / Financial expenses
P4	Pre-tax profits / Financial expenses
P5	Sales / (Financial expenses + Personnel expenses)
BAIIGF	Profits before tax and interest / Financial expenses
DPC	(Cash + Realizable assets) / Short term debt
FPAT	Equity / Total assets

Table 4: Rotated component matrix

	Component								
	1	2	3	4	5	6	7	8	9
RAI	0.935	0.004	-0.076	0.030	0.062	0.230	-0.044	0.003	-0.092
RE	0.930	-0.012	-0.056	0.032	0.069	0.224	-0.084	0.023	-0.062
ROA	0.912	-0.025	-0.037	0.047	0.063	-0.183	-0.043	-0.071	-0.135
L4	0.594	-0.137	-0.160	0.068	0.086	-0.401	0.101	0.306	0.208
FPAT	0.472	0.298	0.092	-0.013	-0.002	0.247	-0.089	-0.235	0.307
L2	0.345	0.283	0.007	0.088	0.008	0.297	0.009	-0.069	0.010
L3	0.055	0.907	0.013	-0.011	-0.009	-0.086	0.060	0.277	0.100
DPC	0.057	0.905	0.010	-0.009	-0.006	-0.089	0.052	0.281	0.094
L1	-0.036	0.800	0.070	0.025	0.051	0.196	0.044	-0.216	-0.059
C1	-0.069	0.797	0.241	-0.052	-0.014	0.194	-0.099	-0.322	-0.093
P5	-0.058	0.090	0.987	-0.043	-0.034	-0.013	0.021	-0.026	0.024
P2	-0.035	0.134	0.844	-0.125	-0.016	0.130	-0.040	-0.150	-0.053
P3	-0.066	0.003	0.817	0.075	-0.044	-0.186	0.088	0.136	0.109
BAIIGF	0.066	-0.008	-0.056	0.992	0.047	-0.010	-0.007	0.020	-0.007
ROAGF	0.058	-0.002	-0.026	0.992	0.038	-0.003	-0.012	0.003	-0.015
P1	0.086	-0.024	-0.021	0.042	0.991	-0.022	0.000	0.022	0.015
REV	0.091	0.047	-0.063	0.043	0.989	0.026	-0.011	0.005	0.003
RRF	0.193	0.059	-0.090	-0.028	0.009	0.860	-0.009	0.148	0.070
L5	-0.150	0.062	0.068	-0.016	0.000	0.008	0.739	0.064	0.079
AU	0.050	-0.017	-0.025	0.003	-0.014	-0.036	0.733	-0.089	-0.128
C2	-0.041	0.061	-0.006	0.013	0.019	0.103	-0.046	0.813	-0.106
FA	0.156	-0.100	-0.181	0.060	-0.084	-0.173	-0.297	0.057	-0.656
P4	-0.012	-0.032	-0.051	0.018	-0.034	-0.064	-0.203	-0.043	0.651

Table 5: Variables assigned to the different factors

Factor 1: RAI, RE, ROA, L4, FPAT, L2
Factor 2: L3, DPC, L1, C1
Factor 3: P5, P2, P3
Factor 4: BAIIGF, ROAGF
Factor 5: P1, REV
Factor 6: RRF
Factor 7: L5, AU
Factor 8: C2
Factor 9: FA, P4

Table 6: Variables assigned to the different factors

Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Factor 9
FPAT	DPC	P5	BAIIGF	P1	RRF	L5	C2	FA

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Table 7: Summary of the model of the complete sample (622 firms)

$$p=\frac{1}{1+e^{-(0,502-10,132FPAT+0,098DPC-0,389P5-33,405RRF-0,681FA)}}$$

Variable	Coefficient β	Wald statistic	Significance	Exp (β)
FPAT	- 10.132	46.579	0.000	0.000
DPC	0.098	25.822	0.000	1.062
P5	- 0.389	5.502	0.019	0.678
RRF	- 33.405	15.671	0.000	0.000
FA	- 0.681	5.936	0.015	0.506

0.5 cutoff point: % of correctly classified cases: 95.30%
Non insolvent firms: 99.70%
Insolvent firms: 44.90%

0.2 cutoff point: % of correctly classified cases: 91.20%
Non insolvent firms: 93.20%
Insolvent firms: 67.30%

Table 8: Summary of the model obtained from the first random half of the sample (311 firms)

$$p=\frac{1}{1+e^{-(0,450-20,270FPAT)}}$$

Variable	Coefficient β	Wald statistic	Significance	Exp (β)
FPAT	- 20.270	27.181	0.000	0.000
0.5 cutoff point:	% of correctly classified cases: 97.10%			
		Non insolvent firms: 99.00%		
		Insolvent firms: 76.00%		
0.2 cutoff point:	% of correctly classified cases: 92.90%			
		Non insolvent firms: 94.10%		
		Insolvent firms: 80.00%		

Table 9: Summary of the model obtained from the second random half of the simple (311 firms)

$$p=\frac{1}{1+e^{-(-1,420-5,806FPAT+0,052DPC-16,214RRF)}}$$

Variable	Coefficient β	Wald statistic	Significance	Exp (β)
FPAT	- 5.806	17.382	0.000	0.003
DPC	0.052	13.120	0.000	1.054
RRF	-16.214	6.131	0.013	0.000
0.5 cutoff point:	% of correctly classified cases: 92.90%			
		Non insolvent firms: 99.30%		
		Insolvent firms: 16.70%		
0.2 cutoff point:	% of correctly classified cases: 92.00%			
		Non insolvent firms: 95.50%		
		Insolvent firms: 50.00%		

Table 10: Summary of balanced simple model (82 firms: 41 insolvent and 41 non insolvent)

$$p=\frac{1}{1+e^{-(10,243-81,340FPAT+2,341DPC)}}$$

Variable	Coefficient β	Wald statistic	Significance	Exp (β)
FPAT	- 81.340	3.147	0.076	0.000
DPC	2.341	1.298	0.255	10.394
0.5 cutoff point:	% of correctly classified cases: 97.60%			
		Non insolvent firms: 97.60%		
		Insolvent firms: 97.60%		