MODELLING OF AN INDICATOR FOR CREDIT SCORING OF NON-FINANCIAL CORPORATIONS – A PRELIMINARY RESEARCH BASED ON DISCRIMINANT ANALYSIS*

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1. INTRODUCTION

A significant share of credit risk in the Portuguese banking system is associated with its exposure to the non-financial corporations. This exposure assumes the form of either credit directly granted (loans and credit lines) or debt securities and equity issued by those corporations and included in the banks' portfolios. At the end of 2006, claims on non financial corporations corresponded to approximately 42 per cent of domestic assets held by resident monetary institutions and 30 per cent of the total assets in the monetary institutions' balance sheets.[1] Detecting the financial fragilities of non-financial corporations, liable to give rise to default in credit payments or even to insolvency, is therefore of the highest relevance in the analysis of the financial stability of the banking system.

In general, the analysis of financial ratios covering different aspects of the position of companies is a key instrument in detecting financial and operational difficulties of non-financial corporations. The use of ratio analysis in the development of techniques for the classification of corporations according to their creditworthiness and to predict business failure and bankruptcy has been increased and is evinced in a number of research since Beaver (1966) and Altman (1968), in the late 1960s, provided the first stimuli to the development of this type of models. Since then, a number of articles have been published with research in this field,[2] which has also been object of special attention by financial institutions and banking supervisors in the framework of the preparation of the new Basel Capital Accord (Basel II), which lays down the implementation of internal risk evaluation models.

Credit risk assessment of an institution requires that the quality of its credit portfolio is known, which will naturally reflect the creditworthiness of the debtors integrating it. This, in turn, depends on the capacity of debtors, at present and within a short- to medium-term horizon, to honour payments on account of interest and principal in due course. The evaluation of this capacity implies the analysis of several aspects of the current position of the company, but it is not easy to reflect them in a synthetic quantitative measure. The scoring models provide these synthetic measures, reflecting several aspects of the position of the company with relevance to gauging its capacity in terms of compliance with credit payments. These models, associated with measures of default probability, make it possible to estimate expected losses within a given time horizon, and are therefore essential instruments in the analysis and management of risk by financial institutions. From the perspective of some central banks, it is also important to mention the additional interest of these models when they form the basis of internal assessment systems of the credits to companies provided as collateral in monetary policy operations.

* The present article has widely benefited from the worthy discussion of a preliminary version within the Financial Stability Unit of the Economics and Research Department. This notwithstanding, the views expressed herein are those of the author and do not necessarily reflect those of Banco de Portugal. Any errors and omissions are the responsibility of the author.

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(1) Resident monetary financial institutions excluding Banco de Portugal.

(2) For a summary of research in this area published in different countries, see Altman and Narayanan (1997).

In addition, the scoring systems of companies based on the respective creditworthiness are a tool for analysis adding to the financial stability aggregate indicators of this sector (usually based on National Financial Accounts statistics). Those models provide a more accurate appreciation of either the trend of risks incurred by the financial system at a given moment in time or their distribution and intensity.

The purpose of the work presented in this article is to estimate synthetic indicators, based on the financial ratios of a set of non-financial corporations, able to signal potential situations of failure in credit payments in some of these companies. In sum, the aim is to obtain indicators which, with acceptable precision, will permit corporations to be classified in one of two groups: failed corporations and non-failed corporations.

The scoring models developed in different countries have an underlying definition of "failure" which is not unique. The "failure" event may correspond to the actual bankruptcy of the company but may also have another nature, such as the non-payment of the debt, whether under the form of debenture or bank loans. Although default in credit payments of a company does not necessarily lead to its bankruptcy, bankruptcy situations of non-financial corporations are, in general, preceded by episodes of default in credit payments which, when persisting and becoming more severe, eventually lead to the extinction of the corporation.[3]

The following section characterises the information used in the development of this article. In particular, it presents some statistics on the data from the Central Balance-Sheet Database of Banco de Portugal and on some financial ratios considered in the estimation process of the score formula. Section 3 describes the methodology followed, while Section 4 presents the results, comparing them with those from the estimation of an equivalent logistic regression model. Chapter 5 presents the conclusions and final comments.

2. DATA

2.1. Characterisation of data used

The dataset used in this study was chiefly from the Central Balance-Sheet Database held by Banco de Portugal and comprises financial statements for a sample of non financial corporations covering the years from 1995 to 2004[4]. It should be noted that this information relates to a sample of companies with some specific characteristics, wherefore some caution is advisable in its analysis and, consequently, in the interpretation of results arising from its utilisation. First, the coverage of all economic activities of non-financial corporations was incomplete until 2000. Only from that date, the sample of the Central Balance Sheet Database has corresponded to a group of companies selected according to statistical representativity criteria. Nonetheless, the sample is clearly biased towards a broader coverage of larger companies, which are exhaustively surveyed, and of some activity sectors (such as manufacturing, "electricity, gas and water" and "transports and communications") to the detriment of other sectors (chiefly "trade and repairs"). In addition to the companies included in the statistical sample, any other non-financial corporation may participate, on its own initiative, in the Central Balance Sheet Database of Banco de Portugal.[5] This possibility permits to widen the coverage of small and medium-sized cor-

(3) See Antunes (2005) on the move from default to recovery and to extinction.
(4) The year 2004 is partly covered.
(5) See Banco de Portugal Booklet No 7 on the Central Balance Sheet Database.

porations (given that these are not the object of exhaustive surveys) and, in view of its strictly voluntary nature, it will tend to cover companies with relatively sound financial positions[6].

Firstly, this article has considered all companies that, at the Central Balance Sheet Database, present validated data, without reporting failures or anomalous values. As regards the companies covered, data on their past credit history was considered, based on principal and interest not paid in due course, as reported to the Central Credit Register (CCR).

Most companies in the initial group (more than 90 per cent) had reported credit liabilities to the CCR at some point during the period under review, of which approximately 15 per cent had a situation of default in credit payments in that period. For the purposes of the present study, the “failure” event in the year (reference period of the financial statements) was defined as the occurrence, during 3 months in a row, of failures in credit payments exceeding 500 euros, on average (reported to the CCR as type 7, 8 or 10 debt)[7].

In order to estimate the model, only data on companies established as regular legal persons was used. Of them, there were excluded those in financial sector (CEA 65, 66 and 67), public administrations (CEA 75), education, health and social work establishments (CEA 80 and 85) and other establishments whose main purpose is in some way similar to the provision of public or collective services (CEA 90, 91 and 92). Additional conditions were required for companies to be included in the samples to be analysed, as described below:

- Average number of employees > 1
- Total net assets > 0
- Debt, excluding intra-group lending and loans granted by other shareholders > 0
- Total equity, including intra-group lending and loans granted by other shareholders > 0
- Sales and provision of goods and services > 0

The sample also excluded companies for which the sum of debts with credit institutions, bonds, equity loans and other loans was nil, but with non-nil registers of credit and interest not paid in due course reported to the CCR in the corresponding year.[8]

Summing up, as a starting point, 133827 observations were analysed relating to 37114 companies. Of these, almost 3000 corresponded to observations with default in credit payments reported in the year, according to the above mentioned definition of the event “failure”. From total companies, 35083 had no report on default episodes in the period considered, corresponding to 125380 observations.

Table 1 presents a summary characterisation of the data initially analysed.

Prior to the estimation of the model, some statistics from a set of financial ratios were analysed, with a view to identifying those that may reveal, à priori, more discriminanting power between failed and non-failed firms. Considering the forward-looking objective of the model, on one hand, and the lag in the availability of the financial information (approximately three quarters after the end of the fiscal year), the financial ratios were considered 1-year lagged from the year when the event characterising the groups occurred.

(6) In turn, companies with significant financial fragilities will tend not to report, especially when their vulnerability becomes more visible. This results in a marked bias of the whole information towards companies with positive creditworthiness, particularly in the case of small- and medium-sized corporations.

(7) It corresponds to credits with late repayment, credits involving litigation and restructured loans. On this subject, see Banco de Portugal Booklet No 5.

(8) A possible cause for this discrepancy may be due to the fact that the balance sheet of companies relates to their position as at the last day of the year, wherefore default situations occurring in any month in the course of the year may have been fully settled at the end of the fiscal year. Other causes may be reporting errors or misclassification in some of the databases used, wherefore observations with this discrepancy were excluded.

Table 1

BRIEF CHARACTERISATION OF ORIGINAL DATA

	Total number of observations	Percentage of observations with default in credit payments during the year	Percentage of observations of firms with no failure in the whole period	Total number of employees (1)	
				Total	*Memo*: Failed firms
1995	12 846	4.3	91.8	39	86
1996	18 162	3.0	93.3	31	64
1997	20 738	2.8	93.9	26	51
1998	21 002	2.2	94.2	27	74
1999	17 760	1.2	94.4	29	64
2000	12 067	1.0	93.5	42	103
2001	11 343	1.4	93.7	42	111
2002	7 170	1.8	94.0	40	107
2003	7 741	2.0	94.1	45	85
2004	4 998	1.9	94.1	48	59

Note: (1) Yearly averages.

2.2. Distribution of main financial ratios

A relatively wide set of financial ratios was considered in the process of selection of indicators with more power to discriminate among credit default situations. In order to avoid an excessive loss of observations, indicators referring to growth rates were not taken into account (which, given the time lag considered, required reporting by the same company for at least three consecutive years). Extreme observations of the ratios on an annual basis were excluded; such outliers were defined by the difference of ± three standard deviations from the average ratio in each year. Nonetheless, a number of indicators maintained quite significant dispersions.

Table 2 presents some distributional measures of the financial ratios initially considered in the modelling process, such as the mean, the median and the standard deviation in the total sample considered. The analysis of the table makes it possible to evince some characteristics of the data included in the initial sample, which shall be the object of some comments.[9]

First, as regards leverage and risk ratios, the indebtedness ratios corresponding to the observations of failed corporations are, on average, higher than in the case of observations without default in credit payments[10]. This was expected, since high financial leverage levels are generally associated with higher default risk.

In addition, the weight of financial debt, on average, is lower in non-failed corporations than in failed corporations. This finding is mostly the result of a significant number of non-failed companies reporting financial debt as nil (almost 40 per cent of the total non-failed); i.e., a significant share of the sample observations relates to companies whose debt to third parties entered in the respective balance-sheets corresponds chiefly to trade credits and intra-group lending and loans granted by associate corporations and shareholders.

(9) Given that, for the purpose of this study, each observation was assimilated to a company (even though relating to the same company, but in different years), observations and corporations shall be mentioned in this section indiscriminately.

(10) In the case of debt ratios as a percentage of total assets – either or not including intra-group lending and loans granted by associate corporations and partners in the debt aggregate –, the dispersion is more marked in the group of observations without default in credit payments. However, the application of the test t to both groups made it possible to confirm the sign of the difference between the groups' average as indicated in Table 2.

Table 2

MAIN FINANCIAL RATIOS

	Without default in credit payments			With default in credit payments		
	Mean	Median	Standard deviation	Mean	Median	Standard deviation
Risk and Leverage ratios						
Debt to third parties, excl. intra - group lending and loans granted by partners / Total net assets	49.0%	50.8%	24.5	66.4%	68.4%	18.2
Debt to third parties, total / Total net assets	61.2%	65.3%	23.8	72.6%	74.6%	16.8
Debt to credit institutions, bonds and equity loans / Total net assets	11.6%	5.1%	14.6	23.4%	21.5%	15.2
Idem, excluding observations with no financial debt	19.0%	16.0%	14.4			
Share of financial debt in total debt to third parties (1)	19.3%	9.0%	23.7	35.7%	32.8%	23.2
Idem, excluding observations with no financial debt	31.4%	26.7%	23.2			
Share of financial debt, including other loans, in total debt to third parties (1)	19.6%	9.4%	24.0	36.4%	34.1%	23.3
Idem, excluding observations with no financial debt	31.9%	27.4%	23.3			
Trade credits (2) / Total net assets	36.3%	33.9%	22.3	40.3%	38.8%	21
Idem, excluding observations with no financial debt	36.1%	34.5%	20.5			
Share of trade credits (2) on total debt to third parties (1)	62.7%	65.2%	29.8	55.2%	56.6%	24.6
Idem, excluding observations with no financial debt	54.9%	56.6%	25.6			
Share of short-term financial debt (3) on total financial debt	27.0%	15.2%	30.4	28.3%	20.3%	28.0
Share of short-term debt to third parties (3) on total debt to third parties (1)	60.1%	64.0%	26.8	57.9%	59.8%	24.8
Equity / Total net assets	33.6%	29.1%	23.1	23.0%	20.7%	16.3
Idem, excluding observations with negative or nil equity	34.1%	29.5%	22.8	23.5%	21.0%	16.0
Equity plus intra - group lending and loans granted by partners / Total net assets	45.7%	43.0%	24.3	29.3%	27.0%	17.8
Idem, excluding observations with negative or nil equity	45.8%	43.1%	24.2	29.4%	27.0%	17.8
Structure ratios						
Debt of third parties, net of provisions / Total net assets	34.5%	32.9%	23.5	34.9%	32.6%	22.4
Debt of third parties, net of provisions / Total debt to third parties	85.7%	58.6%	278	54.7%	49.2%	43.7
Excluding observations in percentile 99	72.0%	58.0%	71.6	54.3%	49.2%	39.7
Debt to third parties, net of provisions / Total net assets less net fixed assets and financial participations	49.4%	52.0%	28.1	56.2%	58.8%	26.5
Equity plus provisions (except for pensions) less total net fixed assets and financial participations / Total net assets	4.5%	4.3%	31.4	-13.3%	-10.8%	27.1
Equity plus intra - group lending and loans granted by other partners less total net fixed assets and financial participations / Total net assets	16.6%	14.7%	31.8	-6.80%	-5.40%	27.6
Liquidity ratios						
Current assets / Total net assets	48.9%	48.5%	26.6	42.4%	39.8%	25.5
Cash, bank deposits and marketable securities / Total net assets	10.3%	5.3%	12.5	4.6%	1.4%	8.4
Profitability ratios						
Net profit / Total net assets	2.7%	1.7%	8.5	-0.9%	0.2%	7.2
EBIT / Total net assets	7.0%	5.7%	10.1	4.9%	5.0%	8.5

Notes: (1) Debt to third parties includes intra-group lending and loans granted by partners (including shareholders). **(2)** Trade debt corresponds to the sum of debts to suppliers, advances from customers and sales account, debt to the State and other public entities and debts to other creditors. **(3)** It only covers observations for which the breakdown of debt into short-term and medium- and long-term is reported.

Considering only the observations with positive financial debt, its weight on total debt (and on total net assets), on average, continues to be higher for failed corporations than for non-failed corporations, although the difference is significantly smaller. In turn, the weight of trade debt on total debt is virtually identical in both groups, when considering only observations with financial debt[11].

As regards the relationship between financial debt and trade credits and the respective impact on the credit quality of companies, economic literature does not provide clear indications on what to expect as regards the difference between the weights of these two liability components in the two groups under analysis. The few research in this field (carried out chiefly in the USA) refers mainly to the significant importance of trade debt as a source of financing of companies, especially small-sized corporations[12].

The two main reasons usually indicated as determining demand for trade credit by companies are the following:

i) The transaction motive: if the timing of delivery of the orders is uncertain and converting liquid assets into cash is costly, companies must hold a high amount of cash balances, permitting immediate and full payment of the orders upon delivery. The utilisation of trade credit permits buyers to save in terms of the transaction costs associated with the maintenance and management of cash balances. For this motive (for which financial credit is no alternative), the share of this type of credit in total liabilities does not provide information on the creditworthiness of companies since its utilisation is a current practice in business. Factors associated namely with the size of the corporation, the turnover and frequency or type of the orders shall determine the intensity of this type of liability in different companies[13].

ii) The financing motive: it refers to the non-utilisation of discounts resulting from the payment in shorter-than-established time-limits, and even the utilisation of trade credit for longer-than-regular time-limits (albeit agreed with suppliers), as an alternative to credit granted by financial institutions. The economic theory associates the use of trade credit for financial reasons (whose implied interest rate is generally higher than in financial debt) to imperfections in the credit market, resulting in credit rationing by financial institutions. Small-sized corporations, on which financial institutions usually have less information than that available to suppliers, are probably more affected by financial credit rationing. For this motive, high balances of trade credit may be associated either with creditworthy companies but with small size – not perfectly evaluated by financial institutions due to lack of information – or with poor credit quality companies. In addition, companies revealing to be “prompt payers” may benefit from especially favourable conditions from their suppliers, for which other factors besides the return on financing may be relevant for the decision to grant credit.[14]

An additional reason for the higher weight of trade debt relative to financial debt in the case of small-sized corporations (which is not directly related to the creditworthiness of the companies) is related to the fact that the amounts of credit needed often are small. Even if funds are available, arrang-

(11) When considering all observations, the weight of trade credits on total debt is naturally higher in the non-failed group than in the failed group, as a result of the high percentage of observations without financial debt in the non-failed group. It should be noted, however, that the weight of intra-group lending and loans granted by other shareholders on debt to third parties is also significantly more relevant when companies do not have financial debt than when they have. In terms of total assets, the trade credits ratio is higher in failed corporations than in non-failed corporations (also, the weight of total debt on assets is higher in the former case). In the case of non-failed corporatios the trade credits ratio on assets is virtually identical in firms either with or without financial debt.

(12) Trade credit is generally granted according to terms that differ among sectors of activity but that typically involve deferred payment up to one month. It involves a discount when payment occurs within a shorter-than-established time-limit; when the normal time-limit is exceeded an additional cost is imposed or restrictions are introduced in the payment of future orders.

(13) Considering that the absence of any time-limit for payment to suppliers, even if small, may reflect a penalty (advance payment or mandatory payment upon delivery) resulting from previous defaults in this type of credit, low levels of utilisation of trade credit might indicate (when compared to similar companies) lack of credit quality of a company.

(14) Lewellen, McConnell and Scott (1980) and Emery (1984) argue that suppliers may charge lower prices than financial institutions for credit granted to risky debtors, because they incur lower risk-evaluation costs due to their access to information, by maintaining regular and close contact with their customers.

ing financial lending involves other costs in addition to the interest rate (such as commissions and other administrative costs related to the opening of files, etc.), which may make closed-end credit from financial institutions significantly more expensive than trade credit, especially if the amount involved is not high enough to offset these costs[15].

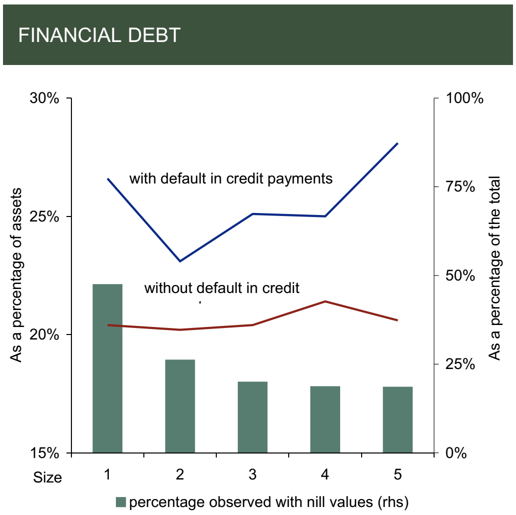
Chart 1 presents the average weights of both financial debt and trade credit on total net assets, by corporation size (evaluated according to the average number of employees in the reference year), for both groups of observations.

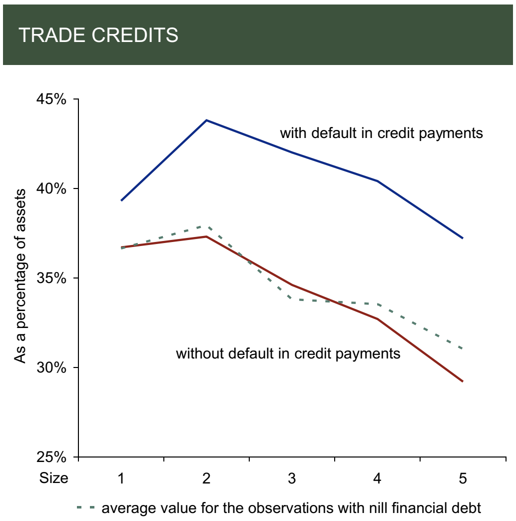
In effect, trade credits has higher weight in total assets in the case of small-sized corporations (considering corporations with more than 20 employees, as a whole).[16] Also, most small-sized corporations do not have financial debt (although the importance of trade credit in total assets is not significantly different, whether or not companies have financial debt). In the case of the sample considered, the absence of financial debt seems to be offset by equity or by intra-group lending and loans granted by partners, the latter with higher relative importance also in the case of small-sized corporations (Chart 2). Failed corporations have on average higher ratios of both financial debt and trade debt than non-failed corporations with both types of debt, so that the ratio of trade credits to financial debt is not particularly different between observations of failed and non-failed firms.

In the sample under analysis, (contrary to economic intuition) the weight of short-term debt (i.e. up to one year) is, on average, higher for the observations without default in credit payments than for the observations with default. This characteristic is maintained even when the failed group includes only observations with positive financial debt, and reflects the quality bias of the companies in the sample.

As regards trade credit granted, the weight in terms of total assets, on average, is not significantly different between both groups of observations. However, the ratio of trade credits granted to those received is higher in the group of observations without default in credit payments than in that of observations with default, indicating that corporations of the first group have more net lending capacity,

Chart 1





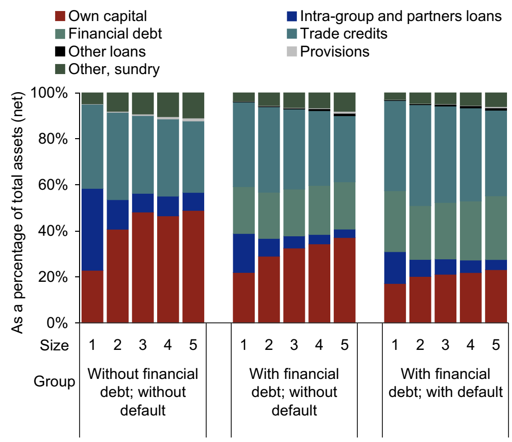
Note: The calculation of the average values of the ratios considered only observations with non-nil ratios.
Size = 1, if <=20 employees; = 2, if >20 and <=50 employees; = 3, if >50 and <=100 employees; =4, if >100 and <=200 employees; =5, if >200 employees.

(15) Credit lines permit this restriction to be eased, since they allow for the partial and fractioned utilisation of lending.

(16) In corporations with less than 20 employees, the weight of the trade debt is relatively smaller, reflecting the higher importance of own funds (including intra-group lending and loans granted by shareholders) in total financial assets.

Chart 2

FINANCING STRUCTURE



Note: Average values of the ratios, for each group (in the group without default in credit payments, observations with and without financial debt were considered separately).
Size = 1, if <=20 employees; = 2, if >20 and <=50 employees; = 3, if >50 and <=100 employees; =4, if >100 and <=200 employees; =5, if >200 employees.

consistent with a sounder financial situation. In terms of current assets, the weight of third-party debt is lower in the non-failed group, reflecting the higher importance of the more liquid assets (such as deposits and securities) in firms in this group. Moreover, own funds (including intra-group lending and loans granted by partners), on average, exceed the value of fixed assets in the case of observations without default in credit payments, contrary to failed corporations, reflecting the poorer financial equilibrium of the latter.

As regards liquidity and profitability ratios, the differences between both groups show the expected sign: failed corporations tend to have less liquidity and lower profitability, in terms of total assets, than non-failed corporations.

3. METHODOLOGY USED

In order to estimate the scoring model from financial ratios, the discriminant function analysis was used. This method consists in estimating a function (the discriminant function) as a liner combination of independent variables (the discriminant variables) able to differentiate an event or individual and classify it in one of two (or more) groups or categories. The groups in question in this study were defined as the one of corporations that failed debt payments and the other of non-failed corporations.[17]

The function to be estimated is of type $L \quad b_1x_1 \quad b_2x_2 \; \ldots\ldots \; b_nx_n \quad c$, where L is a dichotomic variable taking the values 0 and 1 corresponding to the two groups under analysis, b_i are the discriminant coefficients, x_i the discriminant variables and c is a constant. The b_i coefficients are estimated so as to maximise the distance between the group means of the function.

In this study,

(17) This article assumes that each observation corresponds to one company. Although this assumption reduces independence among observations (more markedly after 2000, due to the greater consistency of the sample), it was intended to allow for a higher percentage of observations with default. In addition, observations without default were limited to those with positive financial debt in year t. Moreover. in estimating the discriminant function, less unbalanced samples were used, in terms of the percentage of observations with and without default.

$$L \quad \begin{matrix} 1, \text{ if the firm fails debt payments in the year} \\ 0, \text{ on the contrary} \end{matrix} .$$

Two models were estimated: in a first model, the criterion of distinction between the groups was the occurrence of failure in debt payments in the year, characterised as defaulting debt payments for three consecutive months in a year by an amount greater than 500 euros on average; the second model was intended to analyse the entry into failure in debt payments, defining the group where L 1 as the group in which corporations failed in the year, but not in the previous year.[18] In this case, L was stated as 0 when the firm had not failed in any year over the estimation period. [19]

Both models were estimated twice: with all observations, on one hand, and using only data of the manufacturing branches (CEA 15 to 37), on the other (CEA 15 a 37).

In addition to financial ratios, the estimated models took into account some factors broadly based across observations, such as those associated with the business cycle and with the corporations' sector of activity. For this purpose, the output gap and the short-term interest rate were included as independent variables.[20] Also sectoral dummies were tested in the models considering the observations for all activity sectors.

In addition, logit and probit models were estimated for the same variables, which corroborated the results obtained with the discriminant analysis.

The use of discriminant analysis on a number of ratios covering different features of the firms' financial position made it possible to identify a group of indicators with a significant contribution to the discriminant function.[21] In the final model, the selected ratios relate to indebtedness, asset financing structure, liquidity and profitability.

These ratios were defined as:

$$DIV \quad \frac{\text{Debt to third parties, excluding intra-group lending and loans granted by other partners and shareholders}}{\text{Total net assets}}$$

$$EFA \quad \frac{\text{Equity} \quad \text{intra-group lending and loans granted by other partners and shareholders} \quad \text{total net fixed assets}}{\text{Total net assets}}$$

$$LIQ \quad \frac{\text{Cash, bank deposits and marketable securities}}{\text{Total net assets}}$$

$$ROA \quad \frac{\text{Net profit}}{\text{Total net assets}}$$

(18) The cases in which the company failed debt payments in the year but its situation in the previous year is not observed or also failed (i.e. when it is not possible to determine when the entry into failure in debt payments has occurred or whether it has occurred in the previous year) are excluded. If a company recovers from the default situation within at least one year, and later re-enters into failure in debt payments, this re-entry when immediately preceded by compliance is considered as being an entry of a new company.

(19) In this case, the groups are not mutually exclusive, since the companies that are not in default in the year but were before or will enter into default subsequently are not considered in the group where L = 0.

(20) These two variables are negatively correlated, with the former prevailing in the final model. The coefficients associated with the financial indicators estimated by the models without the business cycle variable are virtually identical to those estimated with that variable, the inclusion of which chiefly influences the value of the constant. The output gap values were calculated using the HP filter to data extracted from the "Quarterly series for the Portuguese economy" (2006) *Banco de Portugal Economic Bulletin Summer* . On this methodology, see *Almeida and Félix (2006)*.

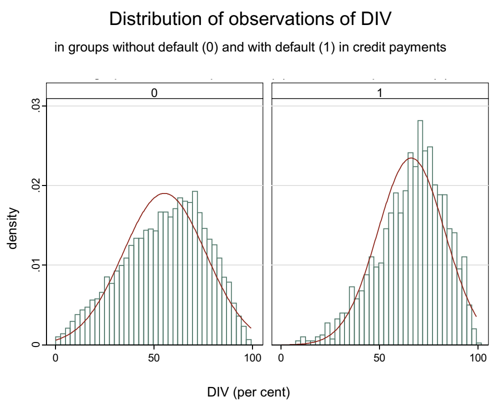
(21) Also the weights of the short-term debt and of intra-group lending and loans granted by shareholders on total debt could satisfactorily differentiate between observations with and without default in credit payments, positively relating to the latter event. However, this discriminanting power is clearly the result of the bias in the quality of firms in the sample, with no economic significance. It was therefore decided not to consider these indicators in the final models.

Moreover, the use of a dummy to differentiate corporations with and without financial debt made it possible to improve the discriminant power of the model (by increasing the number of correct failure predictions). This dummy was assigned to the year t-1 and was defined as follows:

$$dfin \begin{cases} 1, \text{if finacial debt } > 0 \\ 0, \text{if finacial debt } = 0. \end{cases}$$ [22]

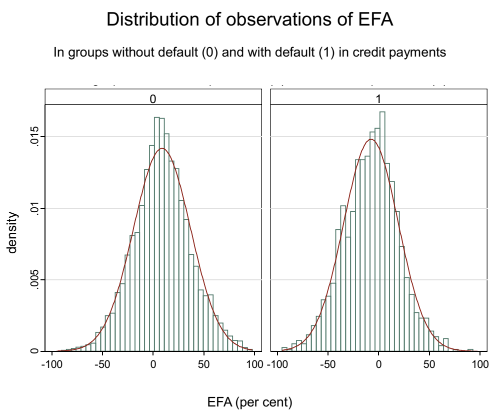
The following charts illustrate the distributions of the mentioned indicators for the set of observations used in estimating the final models, in each of the groups defined by the occurrence of failure in debt payments in the year[23].

Chart 3.1



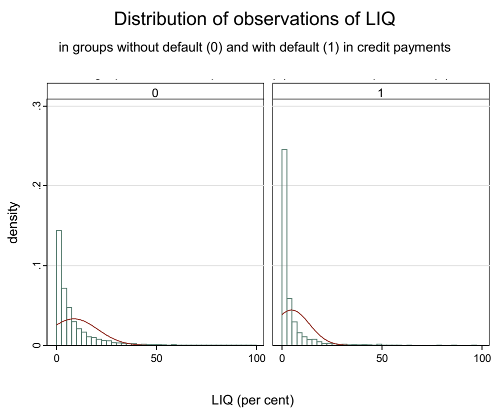
	Without default		With default	
	Mean	Median	Mean	Median
Total	55.3%	57.4%	66.2%	68.2%
Manufacturing	52.3%	53.6%	65.1%	66.0%

Chart 3.2



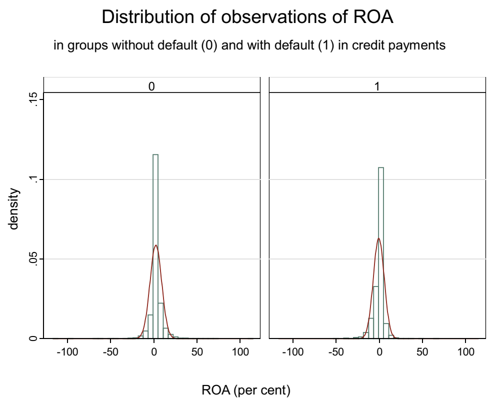
	Without default		With default	
	Mean	Median	Mean	Median
Total	8.7%	8.3%	-7.6%	-6.3%
Manufacturing	4.6%	4.0%	-13.2%	-12.9%

Chart 3.3



	Without default		With default	
	Mean	Median	Mean	Median
Total	8.7%	4.3%	4.8%	1.6%
Manufacturing	7.9%	3.9%	4.0%	1.3%

Chart 3.4



	Without default		With default	
	Mean	Median	Mean	Median
Total	2.20%	1.34%	-0.67%	0.20%
Manufacturing	2.07%	1.26%	-1.37%	0.11%

(22) In this case, the estimated coefficient associated with the dummy is significant and indicates that the probability of a corporation failing credit payments in a given year is higher in the case of corporations carrying forward financial debt from the previous year. From a total of 11443 observations, 1177 corporations reported financial debt in t-1, but did do not report it in t, 11 of which were in default in t.

(23) Charts and statistics presented herein refer to the indicators in t-1 relative to observations for which the financial debt is positive in t, for total observations (charts and statistics) and for observations relative to companies in manufacturing (statistics).

4. RESULTS

The estimated model was identical for both definitions of failure. In effect, the relevant financial ratios selected by the discriminant analysis were the same, whether the dependent variable would refer to the occurrence of failure in debt payments in the year or to the entry into failure in debt payments.

Therefore, the general model estimated is as follows:[24]

$$Z_{i,t} \quad {}_1\,\mathrm{DIV}_{i.t-1} \quad {}_2\,\mathrm{EFA}_{i.t-1} \quad {}_3\,\mathrm{LIQ}_{i,t-1} \quad {}_4\,\mathrm{ROA}_{i,t-1} \quad \mathrm{dfin}_{i,t-1} \quad \mathit{output\ gap}_t$$

The higher the value of $Z_{i,t}$ (corresponding to the estimated score for corporation *i* in year *t*), the higher the probability of failure.

In the case where observations available for all sectors of activity were considered, the model was also estimated with sectoral dummies (dsect_j):

$$Z_{i,t} \quad {}_1\,\mathrm{DIV}_{i.t-1} \quad {}_2\,\mathrm{EFA}_{i.t-1} \quad {}_3\,\mathrm{LIQ}_{i,t-1} \quad {}_4\,\mathrm{ROA}_{i,t-1} \quad \sum_{j\ 1}^{9} {}_j\ \mathrm{dsect}_j \quad \mathrm{dfin}_{i,t-1} \quad \mathit{output\ gap}_t$$

The contribution of some dummies for the discriminant function was little significant, although permitting the percentage of correct in-sample classifications to improve marginally. Also, in the context of the logit model, the inclusion of sectoral dummies was rejected.

Table 3 presents the coefficients estimated for the discriminant function (unstandardised) and for the equivalent logistic regression (i.e. using the same observations), in the case where failure was defined as the occurrence of default in credit payments in the year.[25] The coefficients of the discriminant function reflect the contribution of each ratio for the discriminant score.

The classification power of the model, gauged by the percentage of correct in-sample classifications, stands at around 67 per cent, with a higher percentage (above 71 per cent) in the case of observations belonging to the group of failed.[26] Reflecting the significant disproportion between the sizes of the two groups, the model tends to classify a high percentage of observations without default in credit payments in the failed group.

The coefficients of the model are not significantly changed when the default situation is defined as "entry into failure in debt payments" (Table 4). However, the percentage of correct classifications in the total is, in this case, below 65 per cent (72 per cent in the failed group).[27]

It should be noted that the size of the corporation, which in some research of this nature emerges as a relevant variable to determine the probabilities of default in credit payments (with a negative coefficient), did not have a significant contribution to the discriminant function in this study. In turn, in the case of the logit and probit models, the coefficients of the variable size (measured by the logarithm of

(24) In the case of the model for manufacturing relative to the entry into failure in debt payments, the inclusion of the short-term interest rate instead of the output gap made it possible to obtain marginally better results. However, in order to facilitate comparisons among models, it was decided to consider the model including the output gap.

(25) In order to render more intuitive the interpretation of the scores, these were calculated using the standardised coefficients of the discriminant function instead of the estimated coefficients i (unstandardised). Therefore, the score obtained was positively related to the creditworthiness of the company, where the "cut" value for the purpose of classification in each group is zero. It should be noted, however, that the interpretation of the results, considering the definition of the dependent variable (assuming a nil value in the case of "non-failed" companies and a positive value in the opposite case), indicated that the more negative is the Z-score, the lower is the probability of default. As a result, according to the interpretation of the estimated coefficients (unstandardised), negative contributions (coefficients) for the discriminant function correspond to score improvements, and the opposite in the case of positive coefficients.

(26) As regards the model relating only to observations in manufacturing, the percentage of correct in-sample classifications is slightly higher: 68 per cent of the total, increasing to 74 per cent in the case of observations within the default group.

(27) In the case of manufacturing, the percentage of the total is virtually identical, but rises to approximately 75 per cent in the default group.

Table 3

RESULTS: DISCRIMINANT FUNCTION AND EQUIVALENT LINEAR LOGIT MODEL
Occurrence of failure in debt payments in the year

	Total		Manufacturing	
	Discriminant function	**Logit model** (1)	**Discriminant function**	**Logit model** (1)
	-1.158	-5.132	-1.18	-5.784
		(0.32)		(0.48)
1	1.671	2.063	2.167	2.675
		(0.17)		(0.27)
	-1.294	-1.137	-1.434	-1.369
		(0.12)		(0.18)
3	-1.379	-3.078	-1.474	-4.218
		(0.41)		(0.70)
4	-4.923	-5.379	-5.169	-4.653
		(0.49)		(0.60)
	0.720	2.425	0.393	2.199
		(0.31)		(0.45)
(2)	0.307	0.276	0.238	0.228
		(0.02)		(0.02)

Notes: (1) Numbers in brackets refer to standard deviations. (2) Output gap as a percentage.

the average number of employees) revealed to be significant, although close to zero and with a positive sign, contrarily to that expected (i.e. larger firms have a higher probability to fail in credit payments). This result reflects the characteristics of the sample of the Central Balance Sheet Database, in which, the companies with failure have, on average, more employees than the total, while the smaller companies are typically creditworthy.

Therefore, it is possible to determine a score (which is a synthetic measure of creditworthiness) for each firm, using the formula of the discriminant function to the respective financial ratios. This permit to classify firms into creditworthiness levels, stated as a range of score values with homogeneous probabilities of default in credit payments. The score distribution for each group is illustrated in Charts 4.1 and 4.2.

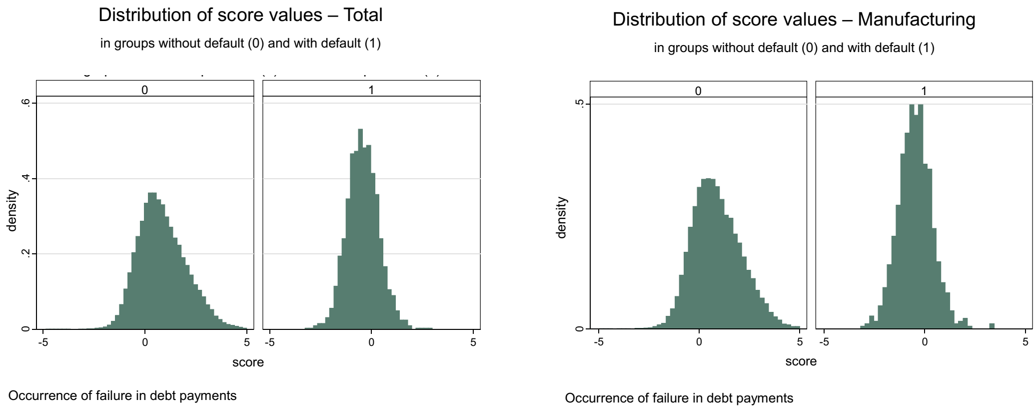
Table 4

RESULTS: DISCRIMINANT FUNCTION AND EQUIVALENT LINEAR LOGIT MODEL
Entry into failure in debt payments in the year

	Total		Manufacturing	
	Discriminant function	**Logit model** (1)	**Discriminant function**	**Logit model** (1)
	-1.395	-5.354	-1.475	-5.796
		(0.34)		(0.51)
1	2.267	2.379	2.775	2.634
		(0.25)		(0.40)
3	-1.150	-0.956	-1.043	-0.864
		(0.17)		(0.28)
3	-1.102	-2.197	-1.569	-3.263
		(0.53)		(0.96)
4	-4.420	-4.240	-5.815	-3.746
		(0.64)		(0.78)
	0.641	1.631	0.431	1.406
		(0.31)		(0.46)
(2)	0.270	0.217	0.147	0.118
		(0.02)		(0.03)

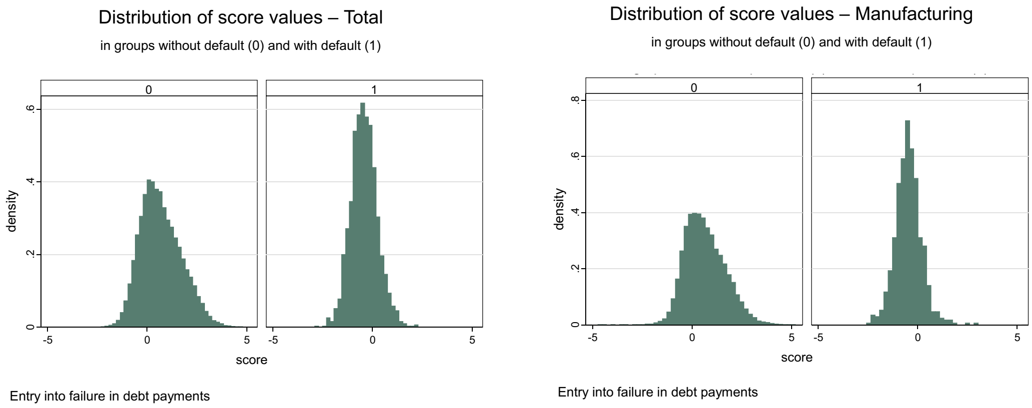
Notes: (1) Numbers in brackets refer to standard deviations. (2) Output gap as a percentage.

Chart 4.1



Note: The calculation of scores is based on standardised coefficients.

Chart 4.2



Note: The calculation of scores is based on standardised coefficients.

In the case of the logistic regression, the estimated model permits observations to be classified according to the value estimated for the probability of occurrence of failure in debt payments. The level of estimated probabilities, in turn, is influenced by the actual proportion of observations with default in credit payments in total observations considered in the model. In order to render comparable the probabilities estimated by the logit models and the percentage of default of the original sample, the estimation of the logistic regression models took into account all observations available in the original sample.

Table 5 presents the percentage of observations with default in credit payments included in each percentile of score values estimated by the discriminant function. It includes also the probabilities of default in credit payments estimated by the logistic regression model for the observations belonging to the percentile.

In the case of the logit model, the inclusion in each of the groups is determined by comparing the estimated probability with the value of the probability selected as cut-off between the two groups. The per-

Table 5

DISTRIBUTION OF OBSERVATIONS WITH DEFAULT IN CREDIT PAYMENTS BY SCORE CLASS

Percentil	Model 1 – total		Model 1 Manufacturing		Model 2 – total		Model 2 Manufacturing	
	Perc.	Logit	Perc.	Logit	Perc.	Logit	Perc.	Logit
[0;10[	10.57	9.88	11.83	10.91	3.94	3.91	3.83	3.57
[10;20[	5.55	5.64	5.88	5.83	2.38	2.28	2.22	2.20
[20;30[	3.87	3.96	4.01	4.05	1.65	1.68	1.85	1.67
[30;40[	3.14	2.96	2.65	2.98	1.56	1.32	1.40	1.33
[40;50[	2.24	2.28	2.56	2.30	1.03	1.04	0.90	1.06
[50;60[	1.63	1.73	1.42	1.69	0.54	0.80	0.74	0.82
[60;70[	1.04	1.23	0.95	1.12	0.49	0.57	0.42	0.61
[70;80[	0.70	0.79	0.60	0.71	0.31	0.37	0.17	0.38
[80;90[	0.36	0.38	0.23	0.34	0.19	0.19	0.15	0.20
[90;100]	0.07	0.07	0.10	0.06	0.03	0.04	0.07	0.04

Note: This table presents the percentage of observations with default in credit payments for each class to which the percentile is the upper limit (model 1: occurrence of failure in debt payments in the year; model 2: entry into failure in debt payments) in total observations in which the estimated score belongs to that class. On the right-hand side, it includes the average value of default probabilities estimated by the logistic regression model for observations included in each percentile class (as a percentage). The score is calculated for all available observations.

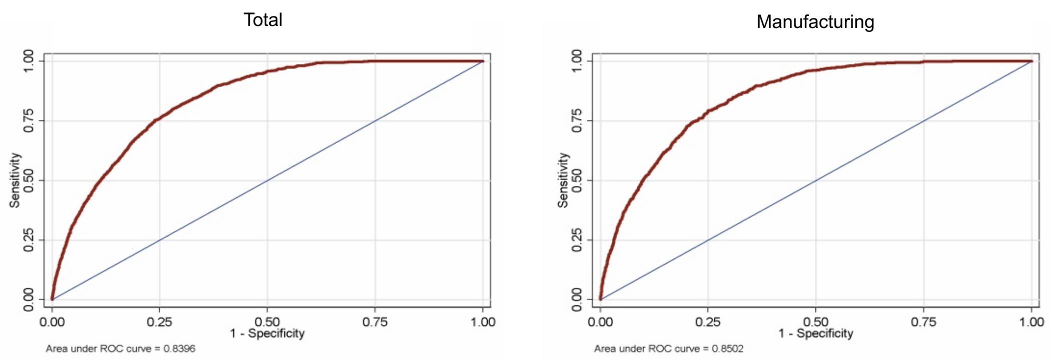
formance of the logit models estimated for the occurrence of failure in debt payments in the year is represented in Chart 5 by the respective ROC curves.[28]

Chart 6 compares the average probability predicted by the logit model for the "occurrence of failure in debt payments in the year" with the percentage of failed companies in the sample in each of the years considered. During the second half of the 1990s, the probability of occurrence of failure in debt payments by non-financial corporations declined systematically, which was supported by the path followed by the interest rate and by the economic juncture. This trend was reversed in 2000, showing a decoupling between the two lines, in particular after 2002. The difference in the profile of the two measures over the last two years of the period under review may reflect somewhat easier conditions provided by financial institutions to companies with fragile financial positions to negotiate the respective loans. This

Chart 5

ROC CURVES

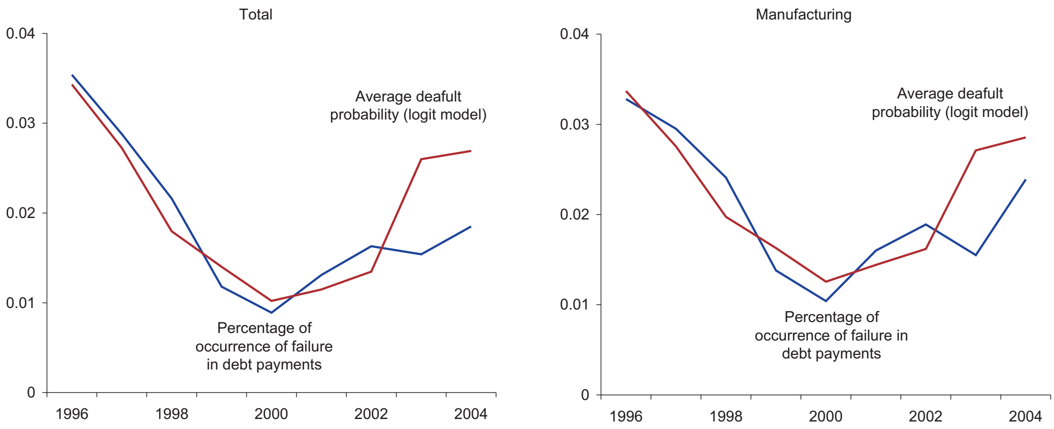
Model relative to the occurrence of failure in debt payments



(28) ROC means Receiver Operating Characteristic. For an intuitive introduction to this topic, see http://www.anaesthetist.com/mnm/stats/roc/.

Chart 6

AVERAGE DEFAULT PROBABILITIES ESTIMATED BY THE LOGIT MODEL
Default in credit payments in the year



development took place against a background of increased competition among banks and of interest rates standing at historically low levels.

5. CONCLUSIONS

The objective of this study was to develop a model aimed at obtaining synthetic indicators on credit risk of the non-financial corporations, by resorting to individual financial information annually disclosed by companies. With this view, a number of financial ratios were analysed in order to gauge their capacity to discriminate companies with higher probability of occurrence of failure in debt payments. A discriminant function was used for this analysis, as well as linear logit/probit models. As expected, more indebted companies will tend to fail debt payments more easily. In turn, companies with higher liquidity and yield ratios will be less liable to enter into failure in debt payments.

This article is a further step into the systematic utilisation of microdata of companies for the purposes of financial stability analysis as well as supervision. However, it has some limitations chiefly resulting from the bias of the sample of firms in the Central Balance-Sheet Database. In particular, data available on financial statements do not cover a significant number of companies with lower credit quality, thus limiting the discriminanting power of the model. The results of this fact are, on the one hand, less conventional signs of the coefficients associated to some indicators (as the case of the weight of short-term debt in the total and the corporation size) and, on the other hand, the little diversified range of indicators kept in the final model (due to the absence of discriminanting power in other indicators covering the more operational aspects of the companies in the sample).

In spite of the limitations due to the characteristics of the information used, the methodology followed permits to define a simple system for the classification of companies based on a score to which a probability of default in credit payments may be associated. The possibility of classifying companies in classes with homogeneous default probabilities has obvious advantages for the supervision of institutions, either because it permits minimum capital requirements to be calculated according to Basle II assumptions, or because it allows for credit provisioning regimes to be defined on the basis of expected losses. Based on the average probability of default in credit payments associated with each score class, the value of debt at risk may be determined at the level of individual companies as the product of that probability by the amount of the financial debt of each company, making it possible to monitor companies of upper risk for the system. The availability of relatively simple financial information on a significant share of indebted companies with specific banking groups will also permit to gauge the amount of debt at risk for these groups and, in aggregate terms, for the system as a whole, thus monitoring it .

The results of this study may be enhanced depending on the additional information made available in the future. Besides incorporating more representative financial information in terms of credit risk (i.e. covering more corporations with default in debt payments), also the inclusion in models of other type of variables, such as the existence of collateral, or of information on other characteristics of the corporation (age, inclusion in a economic group, etc.) will contribute to improve the reliability of results. Monitoring the performance of the estimated models through the inclusion of information relating to subsequent years as it becomes available and applying the methodology to some specific branches of activity will be natural developments of the work presented in this article.

REFERENCES

Almeida, V. and Félix, R. (2006), "Computing Potential Output and the Output Gap for the Portuguese Economy", Banco de Portugal, *Economic Bulletin*, Autumn.

Altman, E. (1968), "Financial ratios, discriminant analysis and the prediction of corporate bankruptcy", *Journal of Finance*, vol. 23, No 4.

Altman, E. (1993), C*orporate Financial Distress and Bankruptcy: A Complete Guide to Predicting and Avoiding Distress and Profiting from Bankruptcy*, 2nd edition, John Wiley & Sons.

Altman, E. and Narayanan, P. (1997), *An International Survey of Business Failure Classification Models, Financial Markets, Institutions & Instruments*, vol. 6, No 2, May.

Artigas, C., and Antuña, A. (2002), "Un sistema de clasificación (rating) de acreditados", Banco de España, *Revista de Estabilidad Financiera*, No 2, May.

Antunes, A. (2005), "A method for the analysis of delinquent firms using multi-state transitions, Banco de Portugal", *Working Paper*.

Antunes, A. and Ribeiro, N. (2004), "Estimates of expected losses in credit portfolios – an application of survival analysis to firms with defaulted credit", Banco de Portugal, *Financial Stability Report*.

Antunes, A., Ribeiro, N. and Antão, P., (2005), "Estimating Probabilities of Default under Macroeconomic Scenarios", Banco de Portugal, *Financial Stability Report*.

Banco de Portugal (2003), "Central Credit Register", Banco de Portugal *Booklet* No 5.

Banco de Portugal (2005), "Central Balance Sheet Database", Banco de Portugal *Booklet* No 7.

Bardos, M. (2001), *Analyse discriminante: Application au risque et scoring financier*, Dunod.

Bardos, M. (2001), "Développements récents de la méthode des scores de la Banque de France", *Bulletin de la Banque de France*, No 90, June.

Bardos, M. (2005), "Les scores de la Banque de France: leur développement, leurs applications, leur maintenance", *Bulletin de la Banque de France,* No 144, December.

Beaver, W. (1966), "Financial ratios as predictors of bankruptcy", *Journal of Accounting Research*, Supplement.

Benito, A., Delgado, F. and Pagés, J. (2004), "A synthetic indicator of financial pressure for Spanish firms", Banco de España, *Working paper* No 411.

Biais, B. and Gollier, C. (1997), "Trade credit and credit rationing", *The Review of Financial Studies*, vol.10, No 4.

Bunn, P. and Redwood, V. (2003), "Company accounts based modelling of business failures and the implications for financial stability", Bank of England, *Working Paper* No 210.

Elliehausen, G. E. and Wolken, J.D. (1993), "The demand for trade credit: an investigation of motives for trade credit use by small businesses", *Board of Governors of the Federal Reserve System*, September.

Emery, G. W. (1984), "A pure financial explanation for trade credit", *Journal of Financial and Quantitative Analysis*, vol. 19, No 3.

Lewellen, W. G., McConnell, J.J. and Scott, J.A. (1980), "Capital market influences on trade credit policies", *Journal of Financial Research*, vol. 3, summer.

Oesterreichische Nationalbank (2004), *Guidelines on Credit Risk Management – Rating Models and Validation*.

Vlieghe, G. W. (2001), "Indicators of fragility in the UK corporate sector", Bank of England, *Working Paper* No 146.