"Internal models (IRB) in Basle II: an approach to determining the probability of default"

AUTHORS	Reyes Samaniego Medina María Dolores Oliver Alfonso María José Váquez Cueto

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
0	0	0

Reyes Samaniego Medina (Spain), María Dolores Oliver Alfonso (Spain), María José Váquez Cueto (Spain)

Internal models (IRB) in Basel II: an approach to determining the probability of default

Abstract

The New Accord of Basel, known as Basel II, opens the way for and encourages the implementation of credit entities' own models for measuring their financial risks. In this paper, we focus on the internal models for the assessment of credit risk (IRB), and specifically on the approach to one of their components: the probability of default (PD).

Our paper is structured in three sections. In the first section, we present the most significant aspects of the credit risk treatment in Basel II. In the second part, the available financial literature is reviewed. And finally, we undertake an empirical application with the object of determining what is or are the variables that are able to explain why a company defaults. Furthermore, this would serve as a preventive "warning system" for financial entities.

Keywords: credit risk, Basel II, probability of default.
JEL Classification: G21, G28.

Introduction

Being aware of the changes that have been taking place in the banking world in recent years, in 1999 the Committee of Basel proposed a restructuring of the 1988 Capital Accord on the measurement and control of the risks faced by financial entities. Thus, in June 2004, the definitive document of the new Accord, known as Basel II, was approved. This Accord is destined to represent a point of departure, not only in the management of risks but also in the relationships those financial entities and their supervisory bodies will have to maintain with each other.

Basel II opens the way for and encourages the implementation of credit entities' own models, known as internal models, for measuring their financial risks. In this paper, we focus on internal models for the assessment of credit risk (IRB – Internal Ratings-Based approach). These models are based on the bank's own estimates and their objective is to calculate the unexpected loss (UL) from credit exposures. The amount of this loss depends on a set of factors: probability of default (PD), loss in the event of default (LGD), exposure at the time of the default or severity (EAD), maturity (M) and granularity (G). In the Accord, the IRB method is put forward in two versions: basic and advanced. Both have in common the need to estimate the probability of default (PD). These estimates must be based on historical data and must represent a conservative view over the medium and long term. The advanced version of IRB also requires the estimate of the rest of the components of the unexpected loss.

Our paper is structured in three sections. In the first section, we present the most notable aspects of the treatment of credit risk in Basel II. The second part comprises a review of the financial literature. And

finally, we carry out an empirical application of the method with the object of determining what is or are the variables that serve to explain why a company defaults and thus, would serve as a preventive "warning system" for financial entities.

1. Credit risk in the new Basel Accord

The treatment of financial risks has now become a strategic factor, not only for bank industry but for any organization, regardless of its size and of the sector in which it undertakes its activity; a factor that can mark the future of any entity. If we focus on the financial entities, there has been an increase in competition, with advances in diversification and liquidity, and there have been very significant changes in the regulations, such as the capital requirements based on the risk. Such factors have stimulated financial entities to seek innovative forms that may help measure and manage all the risks that can influence the growth or survival of their business. Thus, they have recovered a keen interest in risk, for even though risk has existed since banking activity first began, financial entities have not been paying it the attention it deserves. We are speaking here of credit risk.

Credit risk has been the great "forgotten" element in banking practice. The lack of interest in this type of risk is reflected by the fact that the techniques for its measurement and control have hardly evolved at all in the past century. On the contrary, market risk has undergone a significant growth in both its study and in its practical analysis. As a result, financial entities now have available sophisticated mathematical models for its management. However, the current reality is considerably different, for both academics and professionals who have begun to give credit risk the importance that it deserves, and similarly, references to this topic are frequently found in the specialist press. Although the financial entities have now acknowledged the great importance of credit risk, it is by no means easy to

study and measure this key variable, and so there is still a long way to go in this area. Thus, when it comes to measuring market risk, we can undertake studies of the variables that intervene in this, since the necessary historical data exist, but when we speak of credit risk, the question is more complicated due to the lack of historical information to analyze.

The basic objective of the new Basel Accord is to provide a calculation of the necessary bank capital that is more sensitive to the level of risk; to this end it proposes to utilize internal methodologies of risk measurement that are devised by the banks themselves. To achieve this objective without a possible deregulation taking place, the Committee includes in the new Accord elements or techniques that have not previously been taken into account. Thus, the proposal contains novel elements such as:

♦ Internal techniques, with different degrees of assessment, for credit risk.
♦ Credit risk mitigation techniques.
♦ New risks such as operational risk and interest rate risk on investment portfolios.
♦ Two new complementary pillars: Supervisory review process and market discipline.

The determination of the regulatory minimum capital represents an important modification of the 1988 Accord. It establishes methods for calculating the regulatory capital adequate to cover the credit risk. Two methods are foreseen: the first is the *standard,* which is an improvement of that utilized in the previous Accord, and which establishes new categories of risk, grouping each type of company in one or other category. And the second, the *Internal Method or IRB (Internal Rating Based)* based on internal classifications; two levels are considered within this method: *the Basic IRB Method* where the bank calculates some of the variables, but not all, with the rest being provided by the supervisor; and the *Advanced IRB Method*, where the bank calculates all the variables that comprise the model. The Committee hopes that all the entities will, over time, develop and apply the advanced IRB method.

Before explaining the differences between the two variants of the IRB method, it is interesting to recall the various components of credit risk. The first distinction to note is between the expected and unexpected loss. The capital must cover both.

The *expected loss* (*EL*) depends on a series of factors:

♦ *PD*: Probability of default;
♦ *LGD*: Loss give default;
♦ *EAD*: Exposure at default;
♦ *M*: Maturity;
♦ *G*: Granularity.

And the following formula is obtained:

$$EL = PD \times LGD \times EAD . \qquad (1)$$

Or alternatively,

EL = Probability of default x (1- rate of recovery) x amount.

The expected loss (*EL*) is a mean loss whereas the unexpected loss (*IL*) is a maximum loss with a particular level of confidence that is graphically reflected in Figure 1:

IL = Standard deviation of the probability of default x (1 – rate of recovery) x amount of the loan x C, (2)

where *C* is a factor to be estimated, that will be higher as the level of confidence desired is higher.
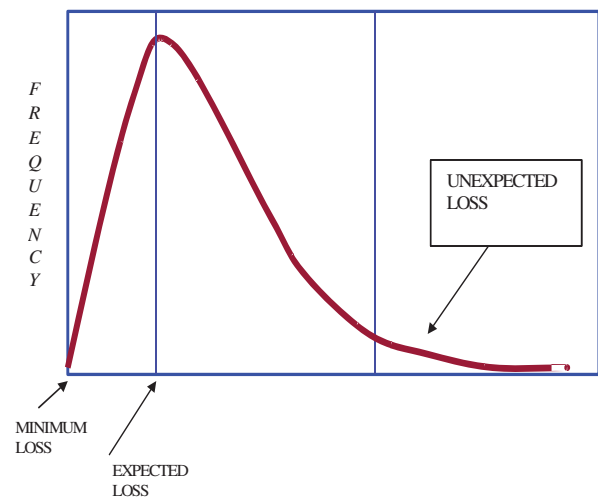

Fig. 1. Expected and unexpected loss in function of the level of confidence

Although the Committee has devised two methodologies for estimating the components of credit risk, basic and advanced, these are only applicable to corporate, banking and sovereign portfolios. In the retail portfolios there is no such distinction between methodologies.

In the basic method the entity only estimates its probabilities of default (PD) while it is the supervisor that provides the values of the rest of the variables. In the advanced methodology, it will be the bank that estimates each of the variables, together with the treatment of any guarantees and credit derivatives.

To be able to utilize either of these methods, the bank must comply with a series of requirements. Thus, it will have to meet certain minima to be able to estimate PD, and some additional ones for estimating each of the remaining variables.

To utilize the IRB method, in either of its two versions, it is necessary to be able to calculate the probability of default. For this, the mean PD of all the loan holders included in a group or level of classifica-

tion must be estimated. These estimates will have to be based on their historical data and represent a conservative view over the medium and long term.

If there are no guarantees or any type of protection for the exposure, the value of PD will correspond to the lower of the two figures: the annual PD associated with the credit rating of the borrower in question, and 0.03%.

2. The treatment of credit risk in the financial literature

A lot has been written on credit risk models in recent years. In fact, Basel establishes its formulation by means of a study conducted among the leading financial entities on the models they are using.

Numerous classifications have been made of the various credit risk models, and one of the most commonly adopted differentiates between structural models and those of reduced form. Thus, Cebedo et al. (2004) define them in the following way:

♦ *Structural models*. Introduced by Merton and developed by, among others, Black and Cox (1976), Geske (1977), Brennan and Schwartz (1980) and Titman and Totous (1989). They aim to obtain the probability of default by means of a model that, for its development, utilizes the value of the company.

♦ *Models of reduced form*. Developed by, among others, Jarrow and Turnbull (1995), Madan and Unal (1998) and Duffie and Singleton (1999). Insolvency is modeled as an exogenous phenomenon. All the theoretical efforts of the models of reduced form are articulated in the modeling of the stochastic process, for insolvency they are associated with the occurrence of this process.

Another equally important classification is where primary models are differentiated from supplementary or additional models. The *primary models* are characterized by obtaining the information needed basically from financial statements of the company. These models are different from the *supplementary or additional models* that extract this information directly from the market.

Among the primary models we find the *univariate models*, which study the behavior of each of the relevant variables separately. The variables to be studied are ratios obtained from the financial statements of companies. This type of analysis allows the analyst to determine, for example, if a particular ratio, for a potential loan, differs substantially from the industry average. One of the classic studies in this respect was written by Beever (1966), who found that, in a sample of companies, a number of indicators could discriminate between healthy and failed companies, in a period of 5-year forecast.

An important advance in the credit risk modeling was marked when the *multivariate models* were applied;

the pioneer work on these types of model was written by Altman in 1968: *Z-Score*. Altman performed a discriminant analysis, considering initially 22 variables (ratios). For this purpose, he selected a sample of 66 companies, 33 failed and 33 healthy. The sample of healthy companies was obtained by seeking to match each failed company with a healthy one of similar size and belonging to the same economic sector.

The model devised by Altman had a great impact, and in fact is still used as a reference in many studies. In this respect, Cebedo et al. (2004) have adapted this model for calculating the probabilities of default in corporations, taking a hypothetical portfolio all belonging to the same sector, with the object of calculating the regulatory capital according to the basic IRB method of the Basel Accord.

However, in recent decades, analysts have generally opted for the logit and probit multivariate models. In this respect, the first to use these types of technique applied to business prediction was Ohlso (1980). Numerous studies have appeared in the financial literature in which these models are utilized. Thus, Wilson (1997) developed the Credit Portfolio View model for McKinsey, establishing a discrete model of numerous periods. With this methodology the probabilities of default are obtained as Logit functions of indices of macroeconomic variables that, in some way, represent the economy performance.

Based on these models, in Spain, we would particularly refer to the more recent work done by Trucarte and Marcelo (2002) and employed by the Bank of Spain. The object of their work is to obtain a system of classification or rating of credit holders (companies) that would serve as an alternative support tool to the new function established in the IRB model proposed by Basel. For this, a logistic regression model is run, such that, from the scores obtained, a classification is established that finally enables homogeneous categories to be obtained; these categories are then used to classify the various credit holders, together with the probability of default assigned to them.

However, this study presents a series of unusual features. On the one hand, financial ratios are not utilized exclusively, but rather three types of discrete variables are introduced additional to the ratios themselves: a fictitious variable to quantify each year covered by the sample being studied, a binary variable of guarantee, reflecting the existence or not of guarantees, and finally, another fictitious variable to denote the sector to which the company belongs. Furthermore, before undertaking the logit analysis, a univariate analysis is conducted to choose the ratio with the best predictive capacity for each category of ratios, which are: profitability, leverage, activity, liquidity, size and productivity.

Fernandez (2005) produced a paper of similar characteristics. This author performs a univariate analysis with the object of choosing, from among the 23 ratios considered to start with, those with the greatest discriminant power, within each of the categories of ratio established[1]. Subsequently, a logit/probit multivariate analysis is performed in order to obtain a score for each company. This permits a system of rating to be established and probabilities of default assigned.

3. Methodology and data

For our work we have taken a sample of companies provided by a Spanish saving bank. From the total we have selected a sample of failed companies, which we have then matched, on the basis of sector and size, with other companies that had not failed. As predictive variables of the probability of failure or default, we have selected a set of financial ratios that cover aspects such as liquidity, degree of leverage, structure of the company, period of rotation, resources generation capacity, and profitability. For each of the failed companies we have calculated the values that these ratios take according to the available data, one period before the default; for this same period the same ratios have been calculated for the healthy "partner" with which it is matched. Thus, we obtain an information table of empirical data, to which we have added the variable indicative of the company's financial health or failure situation. On the basis of the resulting information, and after the appropriate analysis of significance of each variable and tests of correlations between them, we have finally chosen 6 ratios more representative. For these, we present the principal descriptive statistics, comparing the values taken in each of the two groups of companies with which we are working. Finally, and after homogenizing the variables, we have applied a multivariate logit analysis that has provided us with the relative weight or importance of each variable in determining the probability of payment of a company.

Both in the selection of the sample and in the choice of the independent variables utilized in our empirical study, the following approaches have been adopted:

♦ Following Altman (1968), we have paired together, based on size and sector, a number of healthy and failed companies, thus taking a sample with the failed companies representing 50% of the total.

♦ In principle, it appears to be of special relevance, when selecting the sample that the data considered should be obtained for the same period of time in healthy and failed companies alike. However, the companies in bankruptcy tend to delay the presentation of their accounting data in the time period prior to the concursal declaration. To overcome

this inconvenience, we have taken as the accounting data of the last year prior to the failure, the most recent data available.

3.1. Selection of the sample. In the development of our model, we have employed a database provided by a Spanish savings bank that contains information on companies that requested and obtained a loan from this entity. These companies were divided into two groups: healthy and failed. In particular, the sample of failed companies used for the analysis only included those companies with loans from the saving bank whose unpaid debt, whether of interest or principal, amounted to a percentage of more than 10% of the risk granted. The time of computing was December 31, 2003.

The group of healthy companies, that is those that did not generate situations of default in the time horizon considered, was selected by means of individual pairing, controlled by those characteristics that could affect the relationships between financial ratios and failure. Each company of the failed group has been matched with a healthy company of the same industry and same approximate size. In relation to the sector, the pairing was done at a level of four digits of the C.N.A.E. of 1993. The criterion followed for pairing by size is total assets.

As a homogenizing factor for all the companies, we have controlled so that the total of the customer's operations with the saving bank, or live risk, should exceed 60,120 euros, and that they should all be public limited companies (PLT) or limited liability companies (LLC) anonymous or limited companies (S.A. or S.L.), which would facilitate access to their accounting statements.

In total, the sample comprised 106 companies, 53 failed and 53 healthy, with a very diverse spread of economic activities[2].

3.2. Selection of the independent variables of the models. The independent variables chosen for the construction of the models were selected from the financial statements, fundamentally from the Balance Sheet and Profit and Loss Account, of the sampled companies. These accounting statements were extracted from the SABI database which includes more than 95% of the companies that present their accounts in the Mercantile Register in Spain. Given that most of the companies that failed did not present the financial statements the preceding year nor even in the two years prior to the date of default, we have taken the latest data available as corresponding to the year prior to the business failure, as already explained above. Thus, the year t-1 corresponds to that of the latest available accounting statements.

---

[1] Liquidity, leverage, activity, coverage of debt and productivity.

[2] We have excluded from the analysis property development and property sales companies, since these have characteristics that are very peculiar and different from the rest of companies, and because, in the assessment of the application for a loan made by this type of company, the decisive factor for granting the loan is the viability of the specific project for which the loan is sought, and this information is not reflected in the corresponding accounting statements.

The accounting information derived from the sample selected was subjected to a meticulous study with the aim of detecting and resolving, where found, possible anomalies or significant incidents that could distort the final analysis. Those atypical companies with clear and insuperable anomalies in their accounts were excluded from the sample. In this respect, for example, those companies that presented profits despite being in a situation of default were eliminated.

The selection of ratios was made by choosing a broad set of variables (25 in total) that are potentially explanatory variables of business failure based on the frequency and efficacy with which they have been utilized in other predictive models of company insolvency, or in the analysis of banking risks.

The variables utilized include liquidity ratios, leverage, structure, rotation, generation of resources, and profitability. The particular ratios considered in the analysis are given in Table 1.

Table 1. Ratios considered in the analysis

LIQUIDITY RATIOS	Degree to which the company's assets that can be liquidated in the short term are sufficient to meet the payments required for the short-term debts contracted	R1 = Current assets / Current liabilities
		R2 = (Demandable + available assets) / Current liabilities
		R3 = Available assets / Current liabilities
		R4 = (Demandable + Available assets - Current liabilities) / (Operating costs + Personnel costs + Variation provisions + Other operating costs)
RATIOS OF LEVERAGE	Relationship between the different components of the Liabilities, in the short and long term, and the own resources; and between the cost of the debt and the liabilities or the profits and resources generated	R5 = Fixed / Net liabilities
		R6 = Net / Total liabilities
		R7 = Fixed liabilities / (Fixed liabilities + Current liabilities)
		R8 = Financing costs / (Fixed + Current liabilities)
		R9 = Financing costs / (BAIT + Provision for Amortization)
		R10 = Financing costs / BAIT
		R11 = External liabilities / Total liabilities
STRUCTURAL RATIOS	Proportionality between the balance sheet items of assets and liabilities, and in the composition of these items	R12 = (Current assets - Current liabilities) / Total assets.
		R13 = Current assets / Total assets
RATIO OF ROTATION	Measure of the dynamism of the business activity in relation to the structure of the company	R14 = (Current assets - Current liabilities) / (Net turnover + Other income from operations)
RATIOS OF RESOURCE GENERATION	Relationship of the self-financing capacity of the company to various magnitudes	R15 = (Net profit / Loss for period + Amortization provision) / (Net turnover + Other income from operations)
		R16 = (Net profit / Loss for period + Amortization provision) / Current liabilities
		R17 = (Net profit / Loss for period + Amortization provision) / (Fixed liabilities + Current liabilities)
		R18 = (Net profit / Loss for period + Amortization provision) / Total liabilities
		R19 = (BAIT + Amortization provision) / Current liabilities
PROFITABILITY RATIOS	Comparison of the profit obtained at various levels, with the resources invested	R20 = (Operating profit / loss + Financial income + Profits from financial investments + Exchange rate gains) / Total assets
		R21 = Profit / Loss from ordinary activities / Total liabilities
		R22 = Pre-tax profits / Net profits
		R23 = Pre-tax profits / Total liabilities
		R24 = Profit / Loss for the period / Net profits
		R25 = EBIT / Total assets

3.3. Methodology. Following Trucarte and Marcelo (2002), we have firstly applied a univariate analysis to select those ratios that best explain the defaults of these companies. We have complemented this methodology with the presentation of the descriptive statistics of the ratios selected in each subsample selected. Finally, we have applied a logit multivariate analysis to determine the relative importance of those variables chosen as explanatory.

4. Empirical application

To carry out the empirical application we calculate the values of 25 economic-financial ratios (Table 1) for each of the 53 failed companies, for the period immediately before they entered into default, and the same procedure is used for each healthy "paired" company. This produces a table of information containing 106x25 items of data. An additional column indicative of the situation of failure or health of the

company in question is included in the table. Thus, we have assigned the value 0 to the failed company and 1 to the matched healthy company. We thus, obtain an information-decision table of 106x26 items of data.

With this table we set out to determine which one or more of these 25 ratios may serve to explain the failure of a company, and thus, could be used as a preventive warning system for the financial entities with outstanding loans to companies.

In the first place, and given that our intention is to apply classic statistical methods, we have proceeded with the logarithmic transformation of the variables, in an attempt to approach as closely as possible to the required hypotheses of normality on the distributions of the data.

Next, we have proceeded with the localization of *outliers*. At a level of 90%, we have not detected any company in the subsamples that we could consider as an *outlier*.

Having reached this point, we move on to test, using Anovas, the degree of significance of each of the variables considered, with the object of making a first approach to the importance that each variable may have. The results are shown in Table 2.

Table 2. Univariate Anovas

	Wilks' lambda	F	df1	df2	Siq.
R1	,896	12,134	1	104	,001
R2	,882	13,949	1	104	,000
R3	,922	8,841	1	104	,004
R4	,884	13,634	1	104	,000
R5	,999	,145	1	104	,704
R6	,789	27,778	1	104	,000
R7	,997	,273	1	104	,602
R8	,988	1,286	1	104	,259
R9	,958	4,551	1	104	,035
R10	,989	1,158	1	104	,284
R11	,817	23,331	1	104	,000
R12	,860	16,912	1	104	,000
R13	,992	,794	1	104	,375
R14	,949	5,597	1	104	,020
R15	,982	1,902	1	104	,171
R16	,878	14,421	1	104	,000
R17	,828	21,597	1	104	,000
R18	,919	9,111	1	104	,003
R19	,890	12,886	1	104	,001
R20	,877	14,649	1	104	,000
R21	,881	14,077	1	104	,000
R22	,997	,322	1	104	,572
R23	,883	13,836	1	104	,000
R24	,995	,482	1	104	,489
R25	,919	9,195	1	104	,003

Source: Authors' own compilation.

From Table 2 we can see that, at the individual level, the following seventeen ratios turn out to be significant:

♦ liquidity: R1, R2, R3, R4;
♦ leverage: R6, R9, R11;
♦ structure: R12, of rotation: R14;
♦ generation of resources: R16, R17, R18, R19;
♦ profitability: R20, R21, R23, R25.

However, many of these ratios are correlated, and therefore, provide the same information, so they should be eliminated from the final set of ratios selected. To detect these correlations, we have applied the Spearman test of correlation between pairs of variables, utilizing the complete sample.

According to the correlations obtained and the univariate Anovas, we have selected a set of 6 ratios (R16, R17, R18, R14, R19 and R21) to be the ones with which we are finally going to work. These ratios are representative of each of the attributes considered in the companies (liquidity, leverage, structure, rotation, generation of resources and profitability). These ratios are presented in Table 3, where their descriptive statistics in each of the two subsamples considered are also presented.

Table 3. Ratios selected and descriptive statistics

	R4 - 0	R4 - 1	R9 - 0	R9 - 1	R12 - 0	R12 - 1	R14 - 0	R14 - 1	R19 - 0	R19 - 1	R21 - 0	R21 - 1
Minimum	-4.935	-1.262	-3.260	0.000	-1.614	-0.385	-7.036	-0.526	-0.407	0.013	-1.007	-0.033
1st quartile	-0.702	-0.219	0.322	0.086	-0.223	-0.084	-0.296	-0.061	0.026	0.127	-0.042	0.011
Median	-0.326	-0.077	0.517	0.185	-0.087	0.057	-0.057	0.053	0.097	0.228	-0.003	0.031
3rd quartile	-0.105	0.059	0.979	0.393	0.022	0.243	0.029	0.177	0.192	0.551	0.009	0.087
Maximum	0.347	0.797	27.210	0.933	0.600	0.729	1.622	1.016	1.147	1.369	0.329	0.229
Mean	-0.636	-0.092	1.409	0.261	-0.162	0.101	-0.271	0.106	0.147	0.351	-0.046	0.058
CV (standard / mean deviation)	-1.591	-3.609	2.871	0.869	-2.370	2.604	-4.105	2.640	1.734	0.927	-4.136	1.120
Sample variance	1.003	0.108	16.048	0.051	0.144	0.068	1.214	0.077	0.064	0.104	0.036	0.004

Source: Authors' own compilation.

We observe that the ratios behave as expected in the subsamples. For example, the mean value of R4 – ratio of liquidity – is greater in the group of the healthy companies than in that of the failed ones. Similarly, we can check that the mean value of R9 – ratio of leverage – is greater in the failed companies than in the healthy ones.

Once the univariate analysis has been performed, we proceed to combining the information provided by these six ratios by means of a multivariate analysis. From among the various possibilities of modeling offered by classic statistics, we have chosen the logistic analysis. The main reason for this choice is the fact that the variable whose behavior we are trying to predict is binary, and because this model allows us to calculate the probability of default of each company and, as demonstrated in numerous financial analyses, provides good results in terms of correct classification[1].

The equation of the model fitted, once the data are normalized, is as follows:

Prob(healthy company) = exp(eta)/(1+exp(eta)), (3)

where,

eta = -0.559657 + 1.09187*R4 - 2.70022*R9 + 0.577973*R12 - 0.346465*R14 - 0.140624*R19 + 2.06985*R21. (4)

The soundness of the model provides us with the analysis of deviation, shown in Table 4.

Table 4. Analysis of deviation

Source	Deviation	G.l	P-value
Model	47.8226	6	0.0000
Residuals	99.1246	99	0.4776
Total (corr.)	146.947	105	

Source: Authors' own compilation.

Given that the p-value for the model in the analysis of variance table is less than 0.01, there is a statistically significant relationship between the variables, at the 99% level of confidence. In addition, the p-value for the residuals is greater than or equal to 0.10, indicating that the model is not significantly worse than the best possible model for these data, at a 90% or higher level of confidence. The percentage of deviation explained by the model is 32.5441%. This statistic is similar to the usual R-Squared statistic.

From the analysis of the resulting logistic model (equation 4), we observe how the ratios that most influence the probability that the company is healthy are R9 and R21, ratios of leverage and profitability, respectively. The first ratio has a negative sign, that is, the higher its value, the lower the probability that the company is healthy, and the second has a positive sign, that is, the higher its value, the higher the probability that the company is healthy. These are followed in order of importance by the ratios R4 (liquidity) and R12 (structure), both positively influencing the probability of being healthy. Finally,

[1] Several authors argue that the good classification obtained with the logit model explains why it is utilized even though the variables do not specify the initial working hypotheses of the model.

the ratios with least predictive capacity are R14 (rotation) and R19 (generation of resources). These results match those expected.

In addition to the model being significant and explaining an acceptable percentage of deviation, for a cut-off value of 50%, the types I and II errors are good. Table 5 shows the results of the classification according to the logit model. We can confirm that the model successfully predicts 78.30% of the cases; therefore, it can be considered an adequate model for the objective of discriminating between healthy and failed companies. The type I error, that corresponds to assigning incorrectly the condition of financial health to a failed company, is 22.64%. The type II error, derived from classifying a healthy company as failed, reaches 20.75%. Attention is paid to the importance of the type I error, since for any saving bank it will almost certainly be more costly to classify as healthy a company that enters into default, than vice versa.

Table 5. Results of the classification of the logit model with the cases selected

		Forecast group in which the company falls		TOTAL
		failed	healthy	
Observed	failed	41	12	53
	healthy	11	42	53
%	failed	77.36	22.64	100
	healthy	20.75	79.25	100
	Overall correct percentage			78.3

Conclusions

The basic objective of the Basel Committee on Banking Supervision, set out in the new Accord, is to provide a calculation of the required bank capital that is more sensitive to risk. For this purpose, the Accord proposes the utilization of internal methodologies of risk measurement devised by the banks themselves. To achieve this objective without a possible deregulation taking place, the Committee includes in the new Accord elements or techniques that have not previously been taken into account. Thus, innovations such as the inclusion of internal techniques with a different degree of assessment of credit risk appear in the proposal. The Committee has encouraged those entities who use their internal model to estimate previously the *PD, LGD and EAD*.

In the present paper, an empirical analysis is carried out with the objective of determining one of the fundamental variables of the internal models: the probability of default (*PD*). In our work, which is part of a broader line of research, we have sought to determine the variable(s) that may serve to explain why a company defaults and thus, act as preventive "warning system" for financial entities.

The conclusions reached from the utilization of univariate analysis for selecting the ratios that best explain why companies default, complemented with the presentation of the descriptive statistics of the ratios selected, and the performance of a logit multivariate analysis to determine the relative importance of the different variables chosen, are the following:

♦ The ratios that have most weight in the probability that the company is financially healthy are R9 and R21, ratios of leverage and profitability,

respectively. The first ratio has a negative sign, that is, the higher its value, the lower the probability that the company is healthy, and the second has a positive sign, that is, the higher its value, the higher the probability that the company is healthy.

♦ They are followed in order of importance by the ratios R4 (liquidity) and R12 (structure), both affecting positively the probability of being healthy.

♦ Finally, the ratios with least predictive capacity are R14 (rotation) and R19 (generation of resources).

References

1. Altman, E.I. (1968), "Financial Ratios, Discriminate Analysis and the Prediction of Corporate Bankruptcy". *Journal of Finance* (September), pp. 589-609.
2. Basle Committee on Banking Supervision, (1988), "International Convergence of Capital Measurement and Capital Standards". Basle, Julio.
3. Beever, W.H. (1966), "Financial Ratios as Predictors of Failure". *Empirical Research in Accounting: Selected Studies,* (Supplement of The Accounting Review).
4. Black, F., Cox J.C., (1976), "Valuing Corporate Securities: Some Effects of Bond Indenture Provisions," *Journal of Finance* 31, pp. 351-367.
5. Brennan M.J., Schawartz, E.S. (1980), "Analyzing Convertible Bonds". *The Journal of Financial and Quantitative Analysis,* Volume 15, Lumber 4, pp. 907-929.
6. Cebedo, J., Reverte, J.A., Tirado, J.M., (2004), "Riesgo de Crédito y Recursos Propios Mínimos en Entidades Financieras". *Revista Europea de Dirección y Economía de la Empresa,* Volume 13, number 2.
7. Duffie, D., Singleton, K.J., (1999), "Modeling Term Structures of Defaultable Bonds". *The Review of Financial Studies,* Volume 12, Issue 4, pp. 687-720.
8. Fernandez, J.E. (2005), "Corporate Credit Risk Modeling: Quantitative Rating System and Probability of Default Estimation", *DefaultRisk.com, April.*
9. Geske, R. (1977), "The Valuation of Corporate Liabilities as Compound Options", *Journal of Financial and Quantitative Analysis* 12, pp. 541-552.
10. Jarrow, R.A., Turnbull, S.M. (1995), "Pricing derivatives of financial Securities Subject to Credit Risk", *The Journal of finance,* Volume 50, number 1, pp. 53-85.
11. Madan, D.B., Unal, H. (1998), "Pricing the Risk of Default", *Review of Derivatives Research.*, Volume 2, numbers 2-3, pp. 121-160.
12. Merton, R. (1974), "On the Pricing of Corporate Debt: the Risk Structure of Interest Rates", *Journal of Finance* 29, pp. 449-470.
13. Ohlson, J.A. (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy", *Journal of Accounting Research (Spring)*, pp. 109-131.
14. Titman, S., Torous, W. (1989), "Valuing Commercial Mortgages: An Empirical Investigation of the Contingent Claim Approach to Pricing Risky Debt", *Journal of Finance* 44, pp. 345-373.
15. Trucharte, C., Marcelo, A. (2002), "Un Sistema de Clasificación (rating) de Acreditados", *Estabilidad Financiera,* March.
16. Wilson, T. (1997), "Portfolio Credit Risk", *Risk Magazine*, Sept., pp. 111-117.