Credit Concession through credit scoring. Analysis and application proposal[1]

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Abstract

Financial institutions need tools to help them decide in an effective and efficient way concerning time and incurred cost on granting loans to requesting clients. In this sense, credit scoring is a tool of unquestionable interest to those entities. In this paper, we deepen in this technique, propose a multivariate model and validate its usefulness over different samples.

Key words: credit scoring; banking.

[1] Published in Intangible Capital, December 2016.

1. INTRODUCTION

Credit is as old as trade which more or less started in 2000 AC. However, the history of *credit scoring* is very short, just six decades old, Abdou y Pointon (2011). As a consequence of the exponential growth of the demand for credit, financial institutions had the need to develop automated risk evaluation systems (*scoring)* and they had to hire specialized consulting agencies to perform customers evaluation and complex products evaluation (*ratings)* in order to rapidly evaluate the operations and to reduce the cost of analysis.

A *scoring*, also called *credit scoring*, is the assessment of a person or firm asking for financing. This assessment is based on the comparison between the subject asking for credit and previous subjects who asked for credit. It is an automated system of assessment of the credit capacity of the subjects requesting credit operations. Its form and application level varies substantially depending on the institution.

To be more specific, the process of collecting, analyzing and classifying different variables related to credit in order to asses credit decisions is defined as "credit scoring". Actually, there are also other definitions of "credit scoring". For example, Hand & Jacka, (1998, p. 106) says that "the process of modelling creditworthiness is referred to as credit scoring". Anderson (2007) instead says that to define credit scoring, there is the need to break down the term in two parts: credit, meaning "buy now and pay later" and scoring which refers to "the use of a numerical tool to rank order cases according to some real or perceived quality in order to discriminate between them, and ensure objective and consistent decisions".

Given the growing importance of credit activities on the daily operations of credit institutions, it becomes essential the use of models of automated classification which facilitate the concession or not of the credit requested with a high degree of accuracy, so to allow a reduction of defaults, Bonilla et al. (2003); Zhou et al. (2009).

The high risk mortgage crisis (*subprime)* shook the financial stabilities of many developed countries and even if many different factors generated the crisis, it gained relevance the importance of evaluating precisely the risks associated to small credits of banks, Marshall et al. (2010).

In this way, the precise evaluation of the probability of default of banks loans can at least help banks to rank their customers and improve the efficiency of the process related to credit concession. Moreover, a little improvement in the forecasting of the probability of default can bring substantial benefits to the money lender.

Along this line, Blöchlinger & Leippold (2006) study and prove how calibrating the model, a higher discriminant power, translates into an important benefit improvement and it signals that the economic benefits of using *credit scoring* models has been analyzed by various authors.

Without any doubt, it is a good method to help financial institutions giving access to credit to the applicant and to increase the benefits as well as to deny access to credit, so to diminish losses. Wang et al. (2012), signal how the recent world financial *tsunami* generated unprecedented attention to credit risk from financial institutions. In the last years, *credit scoring* has become one of the main tools for financial institutions to assess credit risk, improve the *cash-flow*, reduce possible risks and to make managerial decisions. Another advantage of using *credit scoring* techniques for financial institutions is that it allowed to reach a public not physically close to these institutions, in the sense that it helped the assessment of distance credit. Young et al. (2008) mention that in the last decade, the distance between small businesses asking for credit and banks giving them credit increased substantially. Some of the reasons are a greater level of information and improvement in communication, financial technology and in part the implementation of *credit scoring* models by financial institutions to assess their customers' solvency. In this way, financial institutions get rid of the process which traditionally gave credit only to business physically close to the entity where there was a greater relationship between the two. In addition, the entity would have better awareness of the business applying for credit. In the same way, *scoring* models are useful for financial institutions in developing countries, even if they do not have a long history of credit comparable to the one of the big banks in developed countries, Schreiner (2002), and as shown by Dihn & Kleimeier (2007), there has not been a significant empirical evidence. Therefore, as an example, we can mention Schreiner (2004) for Bolivia and

Viganó (1993) for Burkina Faso. With respect to the fundamental efforts of microfinance institutions in developing countries, it is available Caudill et al. (2012).

As stated by Anderson (2007), the modern world is credit dependent. Entire Economies are led by the ability of some people to buy now and pay later. Lending is a risky business insofar credits applicants defer in their ability to pay and willingness of doing it.

To summarize, the purpose of *credit scoring* is nothing else but classifying credit applicants in two types: Those with good credit, and consequently, higher probability to pay back their financial obligation, and those with bad credit with higher probability of defaulting, Wang et al. (2011). For them, the main objective of their research regarding *credit scoring* was to determine the variables that have significant influence in the probability of default, Thomas (2000); Dihn & Kleimeier (2007).

The rest of the work is organized as follow. In the second part previous works related to *credit scoring* are described. In the third part, the methodology, techniques of analysis and variables are exposed. In the fourth part, the empirical results are analyzed. Finally, in the conclusive part the main results are addressed.

2. PREVIOUS WORK

The main idea behind the concept of credit evaluation is to compare the profile of a customer with the profile of previous customers who received credit in the past and were able to pay it back. Therefore, if a customer has a profile similar to the one that of a previous customer who obtained credit and was able to be solvent, then the financial institution would grant credit, Habdou, H. & Pointon, J. (2011). In order to do so, there is the possibility of applying two techniques: “Loans officer’s subjective assessment and credit scoring” (Crook, 1996). When talking about subjective assessment, it usually means the creditor’s judgmental assessment. The creditor, will have to go through a process which will take into account several factors, both quantitative and qualitative about the individual requesting credit, and it will be driven mainly by the creditor’s experience. The advantage of this approach is that it takes into account also qualitative variables, even behavioral ones which are very difficult to include in a statistical model. On the other hand, a credit scoring model is a more objective and statistically accurate measure to make decisions which has been proven to be the most effective tool credit institutions have to make credit related decisions. To obtain a *scoring,* several statistical techniques are used, starting from the information regarding the applicant (income level, employment history, properties…) and the characteristics of particular loans based on previous operations (payments met, defaults…) to forecast possible future developments. Based on the level of risk the bank wants to take on, the loan is granted or not; and based on the punctuality of the payments, a tariff to pay or a guarantee is established in order to make the operation even safer. The *Scoring* can be applied to both companies and individuals and it is applied in different phases, Amat et al. (2012):

- Customer identification phase. In this phase, financial entities can identify those customers having an appropriate profile to receive the loan.
- Phase of initial study of the operation to decide to accept or not (acceptance *scoring*)
- Once the credit has been granted, there is a phase of post monitoring (Behavioral *scoring*). During this phase, the *scoring* is applied to the customers who obtained the loans and it is useful to assess if it is worth to keep the customer or not, if it is better to increase or reduce the limits allowed, to identify too risky customers before it is too late and establish interests and commissions for the renewals.
- Phase of default. In case the customer defaults, the *scoring* helps to evaluate the level of possible losses and the most appropriate actions to take in order to recover the defaulted payment.

The *scoring* is very generalized for credit to allocate to specific customers, credit cards and mortgages. Based on Fair Isaac Company (2015) data, more than 75% of credit institutions use it to grant mortgages and more than 90% use it for credit cards.
The first *scoring* for credit operations was designed in the USA for the FICO company (1958) and the first *scoring* for credit cards was designed for Montgomery Ward (1960) and for American Bank and Trust (1970). Today, most of the institutions have their own *scoring* system and there are also companies which fill reports about their customers based on their *scorings,* such as Equifax, Experian, Transunion and Axesor.

Other traditional models are the one from Altman (1968) who developed a popular model to forecast the probability of a company to go bankrupt; the one from Argenti (1983) whose aim is to determine the probability of insolvency, using variables related to management and control faults which provoke problems for the company; the Credit – men model proposed by Wall (1928) has the aim to determine the position of a company with respect to other companies operating within the same sector; the Edminster (1972) is a more complex model than the Credit- men proposed because it selects those companies which are similar in certain parameters, while it excludes those which do not meet those parameters; or the Conan & Holder (1979) model, developed in France through the use of discriminant analysis to determine the probability of a company to suspend its interest payments.
Without any doubt, until today, several types of *credit scoring* models have been developed and applied with success to support the approval of credit decisions being one of the main objectives of the *credit scoring* system the classification of samples of similar groups. Generally the problems of the *credit scoring* appear in the classification through statistical methods, Hsieh & Hung(2010).

Below, we show other previous works of international level and what techniques they applied to elaborate the models. In Spain, the appearance of these techniques of automated evaluation is around 1983, Bonilla et al. (2003). The authors make a comparison between parametric models (discriminant analysis and Logit) and non-parametric models (Trees, neural networks; algorithm C4.5...) to determine the concession of credit cards and they conclude that discriminant models resulted to be so powerful in predictive terms that non parametric models do not dominate systematically the parameters.

Hu & Ansell (2007) analyze for the retailing sector the usefulness of the models for credit risk evaluation. In this way, they compare four classical methodologies (Naïve Bayes, logistic regression, recursive partitioning and artificial neuronal networks) with the Sequential Minimal Optimization (SMO). They used a sample of 195 healthy companies and 51 bankrupt from 1994 to 2002. The five methodologies behaved well in predicting bankruptcy, in particular, one year before the event taking place; moreover, it contrasts to how it were possible to predict up to five years in advance the bankruptcy with a level of accuracy superior to 78% and how none of these methodologies resulted to be superior in this classification. This agrees with the previous results where it was posed as a sample how bankruptcy prediction models have a predictive capacity of up to five years before a company goes bankrupt and how it was expected the closest we get to the bankruptcy event the higher the predictive ability, so the values of the ratios deteriorate at a higher intensity, Marín et al. (2011).

Bardos (1998) describes the tools used by the central bank of France during that time to assess credit concessions and built a credit scoring system based on the linear discriminant analysis. Zhou et al. (2009) compare the SVM (support vector machines) technique with six traditional methods, concluding that in general they obtain better results with the previously mentioned technique. On the other hand, Shu-Ting et al. (2009) confirm the excellent results obtained with SVM, but they affirm that through the CLC (Clustering-launched classification) they obtain better results. Paleologo et al. (2010) compares the Subagging technique with other traditional techniques and concludes that with the latter he obtains better results.

In Argentina, Gutiérrez (2008) contrasts the similar results obtained among parametric techniques and uses, starting from the Central Debtors of the Financial system, a model of credit scoring through the Probit. He affirms that in the studies are usually applied parametric techniques instead of non-parametric ones because they are easier to use and to interpret than the more sophisticated non parametric one.

Jacobson y Roszbach (2003) give relevance to how, in general, credit scoring models have the inconvenience of the bias which assumes the sample and they propose a method to give importance to the risk portfolio. They use a sample of 13.338 Swedish credit applicants to whom were granted and refused credit and they apply the Probit method. Their results stress that an efficient selection of the credit applicants can reduce the credit risk up to 80%.

Also through the Probit, Marshall et al. (2010) explore a sample of the UK and the influence of the sample selection bias in the prediction of the probability of default. In Antón (2007) is possible to see how influential are the different decisions that must be taken regarding the final model obtained (Variables and coefficients). For example, variations in the dependent variable, change in the sample of companies, change in the truncation point or the introduction of new variables in the model.

Ochoa et al. (2010) implement a methodology of discriminant analysis to build a scoring model to grant credit, through the statistical analysis of the qualitative and quantitative variables and for a facilitated database for a Colombian financial cooperative.

Wang et al. (2012) analyze an Australian database and a German one in their study, as well as a Chinese database in Wang et al. (2011), and they recognize the wide use in previous studies of discriminant techniques and logit, and they advocate for the use of other techniques less used in the study of credit scoring such as the decision tree showing the usefulness of the latter. Other previous studies such as Zhou et al. (2008), also utilize Australian and German data, and they approach credit scoring through the decision trees technique.

Another study using as data German applicants is the Kim & Son (2003) where, to strengthen the credit scoring management, they develop a credit scoring model through neuronal networks, dividing customers into four subgroups considering their current credit status and the results of the classification.

The study of Blanco et al. (2013) uses neuronal networks as well. They develop several credit scoring models for the microfinance sector using several techniques such as the linear discriminant analysis and the logistic regression. They base their study on a sample of 5.500 loan applicants for a Peruvian microfinance institution, concluding that for the microfinance sector, the results coming from neuronal networks are better than the one obtained with traditional techniques.

Rayo et al. (2010) focus on microfinance institutions (IMFs) and design a credit scoring model for a Peruvian institution under supervision and specialized in microcredit through logistic regression analysis. In this sense, Van Gool et al. (2012), analyze if microfinance institutions can benefit from credit scoring, confirming the absence of quantitative evidence for East Europe, central Asia and Africa. They develop and confirm the validity of the logistic regression models using data from Bosnia

Herzegovina, getting to the conclusion that credit scoring is not able to completely replace the human factor in the process of granting credit and nonetheless is recommendable to introduce these models as tools to improve the process of credit in combination with the human factor.

With respect to the assessment of models, Dryver & Sukkasem (2009) focus on obtaining a better understanding of the existent different methodologies to validate the existing risk models used for credit scoring purposes. Other authors, such as Chuang & Lin (2009) brought up a model of resignation of credit scoring with the aim of improving the correctness of the model classification and to minimize the Type I error .

This report of previous studies is a sample of the diversity of studies related to credit scoring as well as its techniques and variables. A more detailed revision about previous studies can be found in Allen et al. (2004) or more recently in Abdou & Pointon (2011), who analyze 214 articles, books and thesis about statistical techniques and evaluation criteria in credit scoring, concluding, among other things, that it does not exists yet a technique that dominates the others. It also deserves special attention the study of Tascón y Castaño (2012), who realize a large revision of previous studies related to business bankrupcy, models and variables.

3.- Methodology

In order to perform this study, we have used a sample of 80.000 Spanish companies that received a loan from a bank[2] in 2005 and 2006. We have calculated 40 ratios of these companies (see figure 1). These 40 ratios have been identified in the literature review as ratios with more discriminant power. Around 85% of the companies were successful in meeting their interest payments and principal payment at maturity. However, about 15% of them defaulted their credit obligations. To be more specific, based on the Spanish regulation, a firm is considered defaulting their credit obligations when it either does not pay back the principal amount at maturity or, in case of long term loans, it did not meet at least three periodical interest payment.

[2] For confidentiality reasons, the name of the bank is anonymous.

This empirical study has the objective of identifying a function which discriminates the companies based on a higher or lower ability to meet their debt obligations. The companies with higher probability of meeting their obligations will be considered solvent whereas the ones with a lower probability of being able to meet their obligations will be considered insolvent. In this sense, we will try to answer the two following questions:

(1) Which ratios better discriminate the companies based on their being solvent or insolvent?

(2) What is the relative importance of these ratios?

To do that, several statistical techniques with a multifactorial focus have been used (Altman, 1968).

The use of traditional statistical techniques rather than advanced statistical techniques such as neural networks, decision trees and genetic programming can be explained by two reasons. First, there is the aim to follow (Altman, 1968) approach and second because traditional statistical techniques have been proven to have very good performance in the context of the paper. Even if some studies show that advanced statistical techniques have better performance when dealing with predictive abilities. However, other studies have shown that the predicting capabilities of both approaches were sufficiently similar to make it difficult to distinguish between them (Abdou, H. & Pointon, J. (2011).

MANOVA

Discriminant analysis is a simple parametric statistical technique which has been widely used in order to distinguish between bad credit customers and good credit customers, and even nowadays it keeps being considered one of the most appropriate techniques in order to make this kind of distinctions. For this reason, the first two techniques implemented in this paper belong to the family of discriminant analysis techniques and they are MANOVA and LDA.

The Multivariate Analysis of Variance (MANOVA) has been used to detect those independent variables which have a greater discriminant power. In fact, it is a technique used to analyze the relationship between several response variables and common set of predictors at the same time. Let's assume a sample which includes the two different groups (solvent companies and insolvent companies) and where each observation contains different variables (ratios). The question is up to what point these groups are different with respect to these variables. This technique is particularly useful for the identification of the group of variables (ratios) which show a different performance between solvent and insolvent. The variables that show different profiles between the groups are of little utility to discriminate the companies. To sum up, the main objective of the MANOVA analysis is to determine if the response variables, in our case solvent and insolvent firms, are altered by the observer's manipulation of the independent variables which in this study is the possible inclusion or exclusion of certain accounting ratios.

Linear Discriminant Analysis (LDA)

The LDA is a technique which considers the complete profile of the companies and the interactions among the different characteristics. Moreover, the LDA is of great help when there is the need to classify only two groups of companies (in our case solvent and insolvent firms).

Similarly to Altman (1968), a series of ratios that previous literature identified as relevant to forecast insolvency were used. 40 ratios have been used (see figure 1). Following Altman (1968) with the aim to find a final profile of the variables, the statistical significance of the alternative different functions that include the relative contribution of each variable (ratios) have been observed and it was also considered the accuracy of prediction of the different functions.

Figure 1. Ratios used for the empirical study

Financial Ratios	Economic Ratios
1. Current Assets / Current Liabilities	22. COGS / Sales
2. (Receivables + Cash) / Current Liabilities	23. Gross Margin / Sales
3. Cash/ Current Liabilities	24. Employment Cost / Sales
4. (Current Assets – Current Liabilities)/ Current Liabilities	25. Amortization / Sales 26. Losses/ Sales
5. (Current Assets – Current liabilities)/Sales	27. Extraordinary Expenses/ Sales
6. Net Worth/ Total Assets	28. Extraordinary Revenue/ Sales
7. Net Worth / Non-Current Assets	29. Financial Expenses / Sales
8. Net Worth/ Total Liabilities	30. Financial Expenses / Loans
9. Net Worth / Current Liabilities	31. Sales n / Sales n-1
10. Current liabilities / Total Liabilities	32. EBITDA/ Assets

11. (Net profits + Depreciation + Amortization) / Loans 12. (Net Profits + Depreciation + Amortization) / Current liabilities 13. EBITDA / Loans 14. EBITDA / Current Liabilities 15. Sales / Assets 16. Sales / Non-Current Assets 17. Sales / Current Assets 18. Sales/ Inventory 19. COGS / Inventory 20. (Receivables / Sales) x 365 21. (Suppliers /Purchases) x 365	33. EBITDA / Sales 34. EBITDA/ Financial Expenses 35. EBITDA / Net Profits 36. Net profits / Assets 37. Net profits/ Sales 38. Net profits / Net Worth 39. (Net profits – Retained earnings) / Net profits 40. (Net profits- Retained earnings) / Assets

The LDA tries to derive a linear combination of variables (ratios) that maximize the separations between the two groups. The discrimination is reached when meeting the vector that contains the discriminant weight for each one of the independent variables which better separate individual observations result from the two types of companies (solvent and insolvent).

With the aim of evaluating the accuracy of the discriminant model, several alternatives are proposed, which are in the classification matrix (see figure 2), where A and D represent the correct classification. On the contrary, B and C show classification errors:

- A is a company that knows to be insolvent and when the model is applied, the company results insolvent: CORRECT.
- B is a company known to be insolvent, but when the model is applied, the company results solvent: INCORRECT.
- C is a company known to be solvent, but when the model is applied, the company result insolvent: INCORRECT.
- D is a company known to be solvent and when the model is applied, the company results to be solvent: CORRECT.

Figure 2. Companies' classification matrix

	Predicted Group	
Actual Group	**Insolvent**	**Solvent**
Insolvent	A	B
Solvent	C	D

The aim is to identify a model which afterwards can be applied to other companies to predict if those are solvent or insolvent

Logit & Probit Models

Logit & Probit models are conventional techniques used in credit scoring. These techniques find coefficient values such that it is the probability of a unit value of a dichotomous coefficient. Under a Probit model a combination of the independent variables is transformed into its cumulative probability value from a normal distribution. Therefore, they are models of binary election, which is a class of econometrics models where the “dependent” variable is qualitative assuming only two values (0/1). Usually, 1 represent a success while 0 represents a failure. Grablowsky & Talley (1981, p. 260), stated that, under Probit analysis, normal distributions of the “threshold values” are assumed, while multivariate normal distributions and equal variances are assumed under discriminant analysis.

Results

Among all the possible MANOVA combinations the ones with a higher discriminant power were identified. This is a fundamental step for determining which are the accounting ratios that significantly differentiate a solvent firm from an insolvent one. According to our results, the two questions which we tried to answer in this study have the following answers.

(1) Which ratios better discriminate firms based on if they are solvent or insolvent? The four ratios of figure 3 are the one with a higher power to discriminate between solvent and insolvent firms:

Figure 3. Ratios with higher predictive power

Ratio	**Insolvent companies**	**Solvent companies**
Current Assets (CA)/ Current Liabilities (CL)	< 1,2	≥ 1,42
Net worth(NW) / Assets (A)	< 0,3	≥ 0,4
Net profits (NP) / Assets (A)	< 0,01	> 0,05
Net Profits (NP) / Net Worth (NW)	< 0,03	> 0,07

Among the 40 ratios analyzed, these four are the ones which discriminate the most between solvent and insolvent firms.

(2) What is the relative importance of these ratios? The Z formula obtained is the one that best assess an insolvent company when its value is less than zero and it assesses as solvent when the value is above zero.

$$Z = -3{,}9 + 1{,}28\ (CA/CL) + 6{,}1\ (NW/A) + 6{,}5\ (NP/A) + 4{,}8\ (NP/NW)$$

As a consequence, through the discriminant analysis we have identified an integrated function for several ratios that resulted useful to asses if a company can be classified as solvent or insolvent. When the value of the formula above is above zero means that there is a high probability that the company is financially healthy whereas when the value is below zero, there is a high probability that the company has insolvency problems.

To test the usefulness of the model, another sample of 2,000 short term credits issued by the same bank at the end of 2008 were analyzed. Out of these 2.000 short term credits, 144 had problems of insolvency in the time span that goes from the date of issuance till the end of 2010. In figure 4 there is the application of the model at the described loans and the interpretation is as follows: a value of Z equal to 0,8 means that the bank granted a loan to 1,324 companies with a value of Z equal to 0,8 or less. Of these loans, 4 resulted to be defaulting, meaning a 0,8% default rate. Given that the default rate of this list of loans was of 7,2%, if the bank would have demanded a minimum Z score from the companies, it could have reduced the default rate. For example, if the maximum default rate acceptable had been 1,8%, it should not have been granted a loan to any company obtaining a Z score of – 0,8. This means that there would have been issued only 1.747 loans of the 2.000 authorized at the end, and 32 would end up as default loans.

Figure 4. Aplication of the model to Spanish companies in a list of credit of a bank.

Z value	Loans issued	Sum of loans issued	Defaulting loans	Sum of defaulting loans	Percentage of defaulting loans over total loans granted
3,4		0		0	0,0
3,2		0		0	0,0
3	18	18		0	0,0
2,8	53	71		0	0,0
2,6	78	149		0	0,0
2,4	74	223	1	1	0,4
2,2	131	354		1	0,3
2	94	448		1	0,2
1,8	88	536		1	0,2
1,6	152	688		1	0,1
1,4	221	909	2	3	0,3
1,2	181	1090		3	0,3
1	121	1211	1	4	0,3
0,8	113	1324		4	0,3
0,6	96	1420	1	5	0,4
0,4	74	1494	3	8	0,5
0,2	51	1545	2	10	0,6
0	64	1609	1	11	0,7
-0,2	41	1650	5	16	1,0
-0,4	34	1684	4	20	1,2
-0,6	35	1719	8	28	1,6
-0,8	28	1747	4	32	1,8
-1	29	1776	11	43	2,4
-1,2	31	1807	3	46	2,5
-1,4	28	1835	21	67	3,7
-1,6	34	1869	18	85	4,5
-1,8	46	1915	22	107	5,6
-2	13	1928	5	112	5,8
-2,2	39	1967	18	130	6,6
-2,4	25	1992	12	142	7,1
-2,6	8	2000	2	144	7,2
-2,8		2000		144	7,2
-2,8		2000		144	7,2
-3		2000		144	7,2
-3,2		2000		144	7,2
-3,4		2000		144	7,2
-3,6		2000		144	7,2
-3,8		2000		144	7,2
-4		2000		144	7,2

	2000	**2000**	**144**	**144**	**7,2**

It follows another example of use of this kind of scoring. In figure 5 the Z score has been applied to eight Spanish companies. As previously mentioned, a value above zero will be an indicator of a company financially healthy. In the example, a commercial TV station, a textile company, a shopping center chain and a supermarket chain have a value greater than zero and they developed favorably during the years before the measurement. On the contrary, the companies having a negative Z value had less favorable circumstances. An airline company and a real estate company went under bankruptcy in 2010 and 2009, respectively. In Figure 5, it is also possible to see the presence of a Supermarket chain. However, in the case of supermarkets the Z score it is not perfectly applicable because supermarkets get paid soon, tend to obtain an important amount of credit from suppliers and their inventory level is very low. Therefore, it would be interesting as a future development of this work to compute a Z score industry specific, for the supermarket industry for example.

Figure 5: Application of the Z score to eight Spanish firms.

	Commercial TV 2006	Textile Company 2007	Airline Company 2007	Shopping Centers Chain2006	Supermarket chain2008	Airline Company 2006	Real Estate Company 2006	Supermarket Chain 2007
x1 Current Assets / Current liabilities	2,54	1,21	2,11	0,78	0,72	1,5	1,9	0,57
x2 Net Worth/ Assets	0,64	0,59	0,45	0,56	0,38	0,1	0,004	0,31
x3 Net Profits / Assets	0,34	0,18	0,08	0,05	0,07	0,02	0,01	-0,03
x4 Net profits / Net Worth	0,53	0,3	0,17	0,1	0,2	0,03	0,22	-0,09
Z -3,9 + 1,28 x1+ 6,1 x2+ 6,5 x3+ 4,8 x4	8,0092	3,8578	2,8818	1,3194	0,7546	-1,096	-0,3226	-1,9064

A third application of the formula can be seen in figure 6. Basically, it is applied to the values of the healthy firms and with problems which are facilitated in figure 3. As it is possible to double check, companies with problems obtain a negative Z value, whereas the healthy companies obtain a value greater than zero.

Figure 6: Application of the Z score to healthy companies and companies with problems

	Insolvent companies	Solvent companies
Current Assets/ Current Liabilities	1,2	1,42
Net Worth / Assets	0,3	0,4
Net Profits / Assets	0,01	0,05
Net Profits / Net Worth	0,03	0,07
Z -3,9 + 1,28 x1+ 6,1 x2+ 6,5 x3+ 4,8 x4	-0,325	1,0186

5.- Conclusions

It seems unquestionable the growing interest of credit scoring in the last decades as well as the usefulness of these models for financial institutions.

Several statistical techniques have been applied without being able to have constant corroboration until today. In particular, obtaining better results through a technique in particular so to affirm the superiority of one technique with respect to the others. The literature also shows us the best variables for each particular case, but it still does not seem to exist unanimously a set of variables that should always be part of the model. The sample object of the study seems to affect, as previous studies show, the final model obtained.

In this work, a Z model has been developed whose validity has been tested over three different samples, showing a predictive power which can be useful to forecast defaults based on companies ratios. This kind of analysis has to be done with caution because in some sectors the predictions might not be accurate, in the cases where financial practices are very different (when there is rapid cash in from customers, or inventories tend to stay just for a short time in the company, for example). Therefore, we agree with previous studies regarding the importance of the human factor in the process of granting credit. Without any doubt, it is recommendable to introduce these models as a tool to guide the decision making, but only as a complementary tool to the human factor and experience.

Moreover, it would be interesting to try to include behavioral variables within credit scoring models in order to merge the importance of human experience and statistical analysis. There are two other interesting factors to be taken into account. One, given the heterogeneity of the firms analyzed in this study, there is no particular emphasis given to a particular set of accounting ratios. However, if there would be the intention to have a more detailed credit scoring assessment for a specific kind of industry, it would be interesting to repeat the study and obtain a z-score which is industry specific. Two, it might be interesting to evaluate the importance of the variables included in the model because financial institutions might have different ways or priorities when deciding whether to give credit or not. Therefore, a more detailed analysis of the variables might be a powerful tool in order to make credit scoring techniques more and more flexible to the interests of financial institutions.

References

Abdou, H.A. y Pointon, J., 2011: Credit Scoring, statistical techniques and evaluation criteria: A review of the literature, *Intelligent System in Accounting, Finance and Management*, 18, 59-88.

Akhavein, J., Scott, W. y J. White, L., 2005. The Diffusion of Innovations: An Examination of the Adoption of Small Business Credit Scoring by Large Banking Organizations. *The Journal of Business*, 78 (2), 577-596.

Allen, L., DeLong, G. y Saunders, A., 2004. Issues in credit risk modeling of retail markets. *Journal of Banking and Finance*, 28, 727-752.

Altman, E., 1968. Financial ratios, discriminant analysis and the prediction of corporate Bankruptcy. *Journal of Finance,* 23 (7).

Amat, O., Pujadas, P. y Lloret, P., 2012. *Análisis de Operaciones de Crédito*. Barcelona, Profit Editorial.

Anderson, R. 2007. *The Credit Scoring Toolkit: Theory and practice for retail credit risk management and decision automation.* New York, Oxford University Press.

Antón, M., 2007. Una propuesta alternativa en la valoración del riesgo de fracaso empresarial mediante la elaboración y aplicación a priori de modelos de predicción de alerta de crisis. *Revista de Contabilidad y Tributación CEF*, (288), 111-162.

Argenti, J., 1983. Predicting Corporate Failure, Institute of Chartered Accountants in English and Wales. *Accountants Digest, (138).*

Berger, A.N., Klapper, L. y Turk-Ariss, R., 2009. Bank Competition and Financial Stability. *Journal of Financial Services Research*, 35 (2).

Blanco, A., Pino-Mejías, R., Lara, J. y Rayo, S., 2013. Credit scoring models for the microfinance industry using neural networks: Evidence from Peru. *Expert Systems with Applications*, 40, 356-364.

Blöchlinger, A. y Leippold, M., 2006. Economic benefit of powerful credit scoring. *Journal of Banking and Finance*, 30, 851-873.

Bonilla, M, Olmeda, I. y Puertas, R., 2003. Modelos paramétricos y no paramétricos en problemas de Credit Scoring. *Revista Española de Financiación y Contabilidad*, 118 (32), 833-869.

Caudill, S., Gropper, D. y Hartarska, V., 2012. Microfinance institution costs: effects of gender, subsidies and technology, Journal of Financial Economic Policy, 4 (4), 292 – 304.

Chuang, C. y Lin, R., 2009. Constructing a reassigning credit scoring model. *Expert Systems with Applications*, 36, 1685-1694.

Conan, J. y Holder, M., 1979. *Variables explicatives de performance et controle de gestion dans les P.M.I.* Tesis, CERG, Universite Paris Dauphine.

Crook, J. N. 1996. *Credit scoring : An overview*. Working paper series No. 96/13, British Association, Festival of Science. University of Birmingham, The University of Edinburgh

DeYoung, R., Glennon, D. y Nigro, P., 2008. Borrower-lender distance, credit scoring, and loan performance: Evidence from International-opaque small business borrowers. *Journal of Financial Intermediation*, 17, 113-143.

Dinh, T.H.T., Kleimeier, S., 2007. A credit scoring model for Vietnam's retail banking market. *International Review of Financial Analysis*. 16, 471-495.

Dryver, A.L. y Sukkasem, J., 2009. Validating risk models with a focus on credit scoring models. *Journal of Statistical Computation and Simulation*, 2 (79), 181-193.

Edminster, R.O., 1972. An Empirical Test of Financial Ratio Analysis for Small Business Failure Prediction. *Journal of financial and Quantitative analysis*, 2, 1477-1493.

Emel, A. B., Oral, M., Reisman, A., y Yolalan, R., 2003. A credit scoring approach for the commercial banking sector. *Socio-Economic Planning Sciences*, 37, 103–123.

Fair Isaac Company (2015): http://www.myfico.com/CreditEducation/articles/

Grablowsky, B. J., Talley, W. K. 1981. *Probit and discriminant functions for classifying credit applicants: a comparison*. Journal of Economic and Business, 33 (3): 254-261.

Gutiérrez. M.A., 2008. Anatomía de los modelos de credit scoring. Ensayos Económicos BCRA, 50, 61-96.

Hsieh, N. y Hung, L., 2010. A data driven ensemble classifier for credit scoring analysis. *Expert Systems with Applications*, 37, 534-545.

Hu, Y. y Ansell, J., 2007. Measuring retail company performance using credit scoring techniques. *European Journal of Operational Research*, 183, 1595-1606.

Jacobson, T. y Roszbach, K., 2003. Bank lending policy, credit scoring and value-at-risk. *Journal of Banking & Finance*, 27, 615-633.

Kim, Y.S. y Sohn, S.Y., 2004. Managing loan customers using misclassification patterns of credit scoring model. *Expert Systems with Applications*, 26, 567-573.

Lee, T., Chiu, C., Lu, C. y Chen, I., 2002. Credit scoring using the hybrid neural discriminant technique. *Expert Systems with Applications*, 23, 245-254.

Luo, S., Cheng, B. y Hsieh, C., 2009. Prediction model building with clustering-launched classification and support vector machines in credit scoring. *Expert Systems with Applications*, 36, 7562-7566.

Marín, S.; Antón, M y Mondragón, Z., 2011. Crisis bancarias, información financiera y modelos de predicción: estudio de un caso. G*CG: Revista de Globalización, Competitividad y Gobernabilidad*, 5, 32-41.

Marshall, A., Tang, L. y Milne, A., 2010. Variable reduction, simple selection bias and bank retail credit scoring". Journal of Empirical Finance, 17, 501-512.

Medina, R., Trujillo, A. y Martín, J.L., 2006. Un análisis de los modelos contables y de mercado en la evaluación del riesgo de crédito: aplicación al mercado bursátil español. *Revista Europea de Dirección y Economía de la Empresa*, 2 (16), 93-110.

Min J. y Lee, Y., 2008. A practical approach to credit scoring. *Expert Systems with Applications, 35, 1762-1770.*

Ochoa, J.C., Galeano, W. y Agudelo, L.G., 2010. Construcción de un modelo de scoring para el otorgamiento de crédito en una entidad financiera. *Perfil de Coyuntura Económica*, 16, 191-222.

Orgler, Y.E., 1970. A Credit Scoring Model for Comercial Loans. *Journal of Money, Credit and Banking*, 4 (2), 435-445.

Paleologo, G., Elisseeff, A. y Antonini, G., 2010. Subagging for credit scoring models. *European Journal of Operational Research*, 201, 490-499.

Rayo, S., Lara, J. y Camino, D., 2010. Un Modelo de Credit Scoring para instituciones de microfinanzas en el marco de Basilea II. *Journal of Economics, Finance and Administrative Science*, 28 (15), 91-124.

Samaniego, R., Trujillo, A. y Martín, J.L., 2007. Un análisis de los modelos contables y de Mercado en la evaluación del riesgo de crédito: apliación al mercado bursatil español. *Revista Europea de Dirección y Economía de la Empresa*, 16 (2), 93-110.

Schreiner, M., 2002. Ventajas y desventajas del scoring estadístico para las microfinanzas. *Microfinance Risk Management,* Washington University in St. Louis, 1-40.

Schreiner, M., 2004. Scoring arrears at a Microlender in Bolivia. Journal of Microfinance, 6(2), 65-88.

Shu-Ting, L., Cheng, B. y Hsieh, C. 2009. Prediction model building with clustering-launched classification and support vector machines in credit scoring. *Expert Systems with A pplications*, 36, 7562-7566.

Tascón, M y Castaño, F. y Castaño, 2012. Variables y modelos para la identificación y predicción del fracaso empresarial: revisión de la investigación empírica reciente, Revista de Contabilidad, 15 (1),7-58.

Thomas, L.C., 2000. A survey of credit and behavioural scoring: forecasting financial risk of lending to consumers. *International Journal of Forecasting* 16, 149–172.

Van Gool, J., Verbeke, W., Sercu, P. y Baesens, B., 2012. Credit scoring for microfinance: Is it worth it?. *International Journal of Finance and Economics*, 17, 103-123.

Viganó, L., 1993. A credit scoring model for development banks: An African case study. *Savings and Development*, 4, 441−482.

Wah, B., Huat, S. y Mohamed, N.H., 2011. Using data mining to improve assessment of credit worthiness via credit scoring models. *Expert System with Applications*, 38, 13274-13283.

Wall, A., 1928.Ratio method and statement analysys. Harper, Nueva York, 1928.

Wang, G., Hao, J., Ma, J. y Jiang, H., 2011. A comparative assessment of ensemble learning for credit scoring. *Expert System with Applications*, 38, 223-230.

Wang, G., Ma, J., Huang, L. y Xu, K., 2012. Two credit scoring models based on dual strategy ensemble trees. *Knowledge-Based Systems*, 26, 61-68.

Zhou, X., Zhang, D. y Jiang, Y., 2008. A New Credit Scoring Method Based on Rough Sets and Decision Tree. *Advances in Knowledge Discovery and Data Mining*, 5012, 1081-1089

Zhou, L., Lai, K. y Yen, J., 2009. Credit scoring models with AUC maximization based on weighted SVM. *International Journal of Information & Decision Making,* 8 (4), 677-696.