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Credit Scoring for the Supermarket and Retailing Industry: Analysis and Application Proposal[1]

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ABSTRACT

This paper develops and tests a credit scoring model focused on the supermarket and retailing industry which can help financial institutions in assessing credit requests coming from customers belonging to these industries category. The empirical study has the objective of answering two 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 this, several statistical techniques with a multifactorial focus have been applied. The overall approach is the same as the one in Altman (1968), but the application of the design as well as the purpose of it are different. Through the application of several statistical techniques, the credit scoring model has been proved to be effective in assessing credit scoring applications within the supermarket and retailing industry under certain conditions.

KEYWORDS

Credit scoring, Supermarket and retailing industry.

JEL Codes: M14, M41.

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1. Introduction

Credit scoring, is the process of collecting, analyzing and classifying different variables related to credit in order to asses credit decisions, Hand and Jacka, (1998) and Anderson (2007). The importance of this field has been increasing over time reaching its peak during the last financial crisis in 2008 when credit ratings and financial institutions in general showed severe limitations in assessing credit requests and companies' solvency in general. Academic research in the field of credit scoring has the goal of identifying the variables that have significant influence in companies' probability of default, so to allow credit institutions to discriminate between solvent customers and insolvent customers before actually granting credit. In addition, a slightly improvement in the credit scoring assessment leads to significant positive results for the lender (Schreiner, 2002; Schreiner, 2004; De Young, Glennon and Nigro, 2008). However, credit scoring techniques, might be influenced by industry specific characteristics as well as the institution applying it. This paper builds on the work of Amat, Antón and Manini (2016) which addresses the limitation of industry specificity when applying a Z score model for credit scoring purposes. In fact, their model once tested on real companies' data, had extremely high overall results in assessing the solvency of specific companies including the television industry, the airplane industry and much more (Amat, Antón and Manini, 2016). However, this model could not be properly applied to both financial institutions and supermarkets/retailing industries because of their industry specificity. This paper, tries to partially bridge this gap by providing a Z score applicable to the supermarket and retailing industry. The rest of the paper is organized as follow. The second part will briefly revise part of the existing literature in credit scoring. The third part will be dedicated to describing the research methodology and design. Finally, conclusions and limitations of the paper will be discussed.

2. Literature Review

The main idea behind credit scoring is trying to develop a model which can forecast with as high predictive power as possible, if a company will have solvency issues. The most traditional credit scoring models tend to apply a simple basic concept which is comparing customers' profiles. If the profile of a credit applicant is closer to a solvent one then it would be considered solvent, so it would be granted credit otherwise it would be considered not solvent. Hence, the financial institution would deny the credit request (Abdou and Pointon, 2011). To make this kind of comparison, financial institutions can choose between two main techniques. The loans' officer subjective assessment that is the process through which the financial officer in charge after having performed several checks about the credit applicant decides if granting him credit or not. The advantage of this approach is the possibility of taking into account most of the aspects being part of a credit request including qualitative ones (Amat, Antòn, Manini, 2016). The second methodology financial institutions can apply to decide about granting credit or not is the application of a credit scoring model. A statistical model taking into account several factors of the credit application, but mainly relying on quantitative data including historical performance of the credit applicant and financial stability of the latter. Nowadays, more complex statistical models have been developed, but at the same time behavioral science are playing a heavier role within the business science. Therefore, it is still not possible to neutrally and properly decide between the two methodologies without missing some part of the big picture. However, what it is clear is the importance of credit scoring in today's society which is based on borrowing and lending, so on credit and the relevance of credit scoring both in research and applications in the private sector. For instance, the Scoring can be applied to both companies and individuals and it is applied in different phases (Amat, Pujadas and Lloret, 2012):

- Customer identification phase. In this phase, financial entities can identify those customers having an appropriate profile to receive the loan (Arimany and Viladecans, 2015).

- Phase of initial study of the operation to decide whether 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.

Nowadays, many financial institutions have their own credit scoring and there are even some companies such as Experian and Equifax which fill in reports about their customers using credit scoring results. The history of credit scoring started with the FICO score designed in the USA for the FICO company in 1958. The first credit scoring for credit cards instead started in 1960 with Montgomery Ward. Still today, there is significant dispute among scholars and practitioners about what is the best statistical technique to apply to obtain the best credit scoring model in terms of predicting power. One of the most famous and respected credit scoring model is the Z score of Altman (1968) whose model is still one of the most used by credit institutions. Argenti (1983) proposed a model which aims at determining the probability of insolvency of a company using variables related to management and control. Along this line many others credit scoring models have been developed trying to add value to the previous ones. For instance, Hu and 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 that went bankrupt between 1994 to 2002. The five methodologies behaved well in predicting bankruptcy, in particular, one year before the event took place; moreover, it contrasts to how it was 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 that the closer we get to the bankruptcy event the higher the predictive ability, so the values of the ratios deteriorate at a higher intensity (Marín, Antón and Mondragón, 2011), (Amat, Antón and Manini, 2016). The rest of this section will briefly describe some of the more interesting academic works related to credits scoring. For instance, in Spain among the first appearances of credit scoring techniques of automated valuation we can mention Bonilla, Olmeda and Puertas (2003). As briefly mentioned before, many of the most relevant academic contributions in credit scoring research attempt to develop, compare and comment on the statistical approaches to be used in order to obtain models yielding every time higher predictive power. Bardos (1998) develops a credit scoring model based on linear discriminant analysis after describing the tool used by the Central Bank of France to assess credit concessions. Zhou, Lai and Yen (2009) compare the SVM (support vector machines) technique with six traditional methods, concluding that the SVM approach yields better results than the traditional techniques. On the other hand, Shu-Ting, Cheng and Hsieh (2009) confirm the excellent results obtained with SVM, but they affirm that through the CLC (Clustering-launched classification) better results can be achieved. Paleologo, Elisseeff and Antonini (2010) compare the Subagging technique with other traditional techniques concluding that the latter approach yields higher predictive power. A very interesting contribution to the field of credit scoring, is Gutierrez (2008) who discusses the application of non-parametric techniques in credit scoring. He develops a model based on the Probit model and also comments on the dominance of parametric techniques in the field. His opinion is that parametric techniques are the most used because they are easier to apply and interpret. Antón (2007) shows how influential are the different decisions regarding coefficients and variables for the final outcome of a credit scoring model. Ochoa, Galeano and Agudelo (2010) adopt a discriminant analysis approach to develop a credit scoring model which includes not only the statistical analysis of quantitative variables, but also qualitative ones. The work mentioned so far, focuses mostly on traditional techniques including LDA and Probit model. However, throughout the development of the field, some researchers tried to develop models using more complex techniques such as neuronal networks and decision trees. For example, the study of Blanco, Pino-Mejías, Lara and Rayo (2013) uses neuronal networks. They develop several credit scoring models for the microfinance sector using different techniques including 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 yield better results than those obtained applying traditional techniques. Given that the main purpose of this paper is not to carefully review the existing literature in credit scoring, some of the main contributions in the literature have just been briefly described in order to give the reader a sense of the progresses and changes in general the field have been going through. However, in case the reader is interested in deepening his knowledge of the field analyzing the existing credit scoring literature, a more detailed revision of such works can be found in Allen, De Long and Sanders (2008) and more recently in Abdou and Pointon (2011).

3. Methodology

As Amat, Antón and Manini (2016) this study has the aim of identifying a function which discriminates the companies based on their ability of being solvent. Companies with higher probability to meet their debt obligations will be considered solvent whereas companies yielding lower a probability of meeting their debt obligations will be considered insolvent. To do so, this paper will try to answer the following questions:

1) Which ratios better discriminate the companies based on their degree of solvency?
2) What is the relative importance of these ratios?

To answer these two questions, the authors decided to follow as faithfully as possible the Altman (1968) approach.

4. Data

To perform the analysis, we use data coming from the SABI database focusing on companies operating in the following industries:

1) Retail sale in non-specialized store (industry classification 471)
2) Retail sale of food, beverages and tobacco in specialized store (industry classification 472)

Information are gathered on balance sheet information needed for building ratios from 1 to 40* and related to the period 2005-2006. The choice of using these 40 ratios (see Table 1) reflects the aim of the authors to follow the Altman approach and to continue the work started by Amat, Antón and Manini (2016).

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
5. (Current Assets – Current liabilities)/Sales	26. Losses/ Sales
6. Net Worth/ Total Assets	27. Extraordinary Expenses/ Sales
7. Net Worth / Non-Current Assets	28. Extraordinary Revenue/ Sales
8. Net Worth/ Total Liabilities	29. Financial Expenses / Sales
9. Net Worth / Current Liabilities	30. Financial Expenses / Loans
10. Current liabilities / Total Liabilities	31. Sales n / Sales n-1
11. (Net profits + Depreciation + Amortization) / Loans	32. EBITDA/ Assets
12. (Net Profits + Depreciation + Amortization) / Current liabilities	33. EBITDA / Sales
13. EBITDA / Loans	34. EBITDA/ Financial Expenses
14. EBITDA / Current Liabilities	35. EBITDA / Net Profits
15. Sales / Assets	36. Net profits / Assets
16. Sales / Non-Current Assets	37. Net profits/ Sales
17. Sales / Current Assets	38. Net profits / Net Worth
18. Sales/ Inventory	39. (Net profits – Retained earnings) / Net profits
19. COGS / Inventory	40. (Net profits- Retained earnings) / Assets
20. (Receivables / Sales) x 365	
21. (Suppliers /Purchases) x 365	

Table 1. Ratios tested
Source: Amat, Antón and Manini (2016)

The time interval has been chosen taking into account the proximity to the last financial crises, so the effects it should have had on the Z score of the companies, but avoiding the big impact the crisis itself might have generated. Therefore, we consider it an appropriate time period to check for the robustness of our model and at the same time avoiding abnormal distortions which the financial crisis might generate to our analysis. Balance sheet data are deflated to keep track of inflation and cleaned according to standard procedure described in (Kalemli-Ozcan, 2015). The initial dataset comprises 33,397 companies. Data are winsorized each year at the 1^{st} and 99^{th} percentile to avoid extreme observations. Due to lack of information on receivables, COGS, suppliers, purchases and retained earnings, we start with no observation for ratios: 2, 18, 19, 20, 21, 22, 23, 39 and 40. For identifying bankrupt companies, we build a dummy (failed) taking the value one if the company is registered with one of the following status at any point in time in our dataset:

- Bankruptcy
- The company is going through a judicial dissolution process
- The company through liquidation of insolvency proceedings
- The company is immerse in an insolvency proceeding
- The company is going through an ipso jure dissolution process

- Insolvency proceedings
- Suspension of payments

Overall, we end up with 182 bankrupt companies. However, in the analysis will appear only 100 companies because not every firm year entry in the dataset has information in all remained ratios. Therefore, we select a subsample of companies with information for most of the ratios and we will end up with 18 ratios for our final analysis. Basically, the 18 final ratios are those for which we have the most information available.

5. Analysis and Results

As mentioned previously, the sample of bankruptcy companies which will be used in the analysis is of 100 observations. Also, this paper tries to be as faithful as possible to Altman (1968). Hence, data about the bankruptcy companies refer to one year before the bankruptcy. In order to identify the year of bankruptcy, we fix it as the last year for which there are information on total assets, as data on timing of status are sparse and unreliable. Due to the higher number of observation on active companies compared to bankruptcy ones, we can choose those observations that best match the distribution of total assets such as size in the spirit of Altman (1986). We do this by selecting for each bankrupt company an active one with closest size in absolute terms. Therefore, our analysis will be based on 200 different companies with nearly identical size distribution (see Table 2)

VARIABLES	(1) N	(2) min	(3) max	(4) mean	(5) median	(6) sd
Bankrupt	100	6.569	15.14	11.37	11.42	1.580
Active	100	6.568	15.14	11.37	11.42	1.580

Table 2. Summary statistics of log (total assets)

Given these premises, we perform linear discriminant analysis (LDA) to discriminate between active and bankrupt companies. The null hypothesis that they are not jointly statistically significant is rejected at any level of confidence (result not reported)- the related statistic is reported as λ in (Altman, 1968). In Table 3 we report the standardized coefficients from LDA and the p-value from the F test with null hypothesis stating that the average ratio is equal across bankrupt companies and active.

	STD. COEF.	P-VALUE
RATIO1	0.703968427	0.020204116
RATIO3	-1.003429488	0.059259599
RATIO5	0.091278437	0.04087673
ARATIO6	-0.674370337	3.69252E-05
RATIO7	-0.534358913	0.087573142
RATIO8	0.015150497	0.000126452
RATIO9	-0.482517427	0.000569237
RATIO10	-0.035499329	0.950261387
RATIO14	-0.533478941	0.000612839
RATIO15	-0.011081069	0.510669007
RATIO16	0.362355194	0.166521509
RATIO17	-0.136017263	0.482103071
RATIO24	-0.245697896	0.033266784
RATIO29	0.279078705	0.08772382
RATIO31	-0.255301279	0.154368634
RATIO32	0.483550515	0.018107832
RATIO33	-0.143635301	0.016346925
RATIO34	-0.240578591	0.067384031

Table 3. Standardied coefficients from LDA and p-values from bilateral t-test on mean

At this stage, we aim at reducing the dimensionality of the problem, so we select only those ratios with p-value close or smaller than 5%. When we have different ratios with the same numerator, we retain the one with highest absolute standardized coefficient. This strategy leaves us with 6 ratios for the final analysis.

- Ratio 1: Current Assets/Current Liabilities
- Ratio 3: Cash/Current liabilities
- Ratio 5: Working Capital/Sales
- Ratio 6: Net Worth/Assets
- Ratio 14: EBITDA/Current liabilities
- Ratio 24: Employment Costs/ Sales

We now perform the LDA using only these 6 ratios. The group centroids are the following (Table 4).

active	failed	λ
-.4336523	4336523	6.1102***

Table 4. Group centroids

Again, the λ statistic implies that the ratios are jointly significant at any level of significance. Notice that the negative centroid for active firms means that an increase in a given ratio implies a reduction of the probability of bankruptcy if the related standardized coefficient is negative and an increase if positive. The final Z function considering standardized coefficients as in Table 3 is the following:

Z= 0.103 * Ratio1 - 0.671 * Ratio3 - 0.079 * Ratio5 - 0.460 * Ratio6 -0.692 * Ratio14 + 0.273 * Ratio24

A high level of EBITDA/Current Liabilities (Ratio 14) and Cash/Current Liabilities (Ratio 3) are the best predictor of firms that are not bankrupt against those that are. The classification is the following (Table 5).

True \ Classified	active	failed	total
active	71	29	100
failed	38	62	100

Table 5. Classification between active and failed companies using the algorithm

Hence our algorithm correctly identifies 62% of bankruptcy companies and 71% of active companies. As a further check, we apply the algorithm to bankrupt firms in the sample 2 and 3 years before the bankruptcy. The results are described as follows (Table 6 and Table 7).

	active	failed	total
N	32	64	96
%	33.3	66.7	100

Table 6. Classification of ex-post bankrupt companies 2 years before the bankruptcy

	active	failed	total
N	39	33	72
%	54.2	45.8	100

Table 7. Classification of ex-post bankrupt companies 3 years before the bankruptcy

As expected, moving from 3 to 2 years prior to bankruptcy, the percentage of companies correctly identified as bankrupt increases from 45,8% to 66,7%.

The percentage of predicted bankruptcies increases rapidly one year before the bankruptcy itself. We observe a similar trend for the median Z-score, whereas the average Z-score depicts an inconsistent trend, but that is influenced by extreme realizations on the left tail (Table 8).

	t = 4	t=3	t=2	t=1
% (N)	50 (19)	50.98 (26)	45.83 (33)	66.67 (64)
Average Z	0.04	0.18	-0.07	-0.108
Median Z	-0.006	.0039082	-.0200121	.118043

Table 8. Classification and average and median Z-score of bankrupt companies t years before bankruptcy

Note that sample size reduces when we move backward before bankruptcy, as we lose track of some firms balance sheet data.

6. Conclusions

This paper tries to complete the work started by Amat, Antón and Manini (2016) building a Z score which could help financial institutions assessing the solvency of companies within the supermarket and retailing industry. This is definitely a step further towards the cooperation between research and private sector and the results achieved show that the model is fairly reliable considering some limitations such as industry specificity. In fact this particular model is meant only for the supermarket and retailing industry. The geographical location of the companies analyzed, in fact the sample analyzed belong mostly to the Spanish market. Lastly, the methodology applied is a traditional one which is still the guideline within the credit scoring applications, but it is clear that academic research in credit scoring is trying to go other ways exploiting the growing knowledge on applied statistics and big data. Finally, some limitations can be considered. For example, this study focuses on companies within the Spanish market operating in a very specific industry field. Moreover, the statistical approach of the study follows the structure of both Altman (1968) and Amat, Antón and Manini (2016).

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