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Analysis of the Economic Sustainability of the Supply Chain Sector by Applying the Altman Z-Score Predictor

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Abstract: This paper fills the gap in the financial perspective of supply chain performance measurement, related to the lack of a bankruptcy probability indicator, and proposes a predictor which is the eighth-model of the Altman Z-Score Logistic Regression. Furthermore, a bankruptcy probability ranking is established for the companies' supply chains, according to the industry to which they belong. Moreover, the values are set to establish three categories of companies according to predictor. The probability of bankruptcy is analysed and studied for the supply chain of different industries. The building industry is revealed to have the highest probability of bankruptcy.

Keywords: bankruptcy; risk prediction; supply chain; Altman's Z-score



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1. Introduction

The definition of “supply chain” has been widely established in the state of the art as a network of materials, information and services linked in three states: procurement, production and distribution. The most complex supply chain is the one called the ultimate supply chain, which includes the entire sector of companies from different industries that pertain to all flows of products, services, finance and information from the ultimate suppliers to the ultimate customers [1,2].

The sector of the supply chain called the ultimate supply chain represents the alignment of multiple companies that bring products or services to the ultimate consumers in the market. The industries to which the companies in the ultimate supply chain belong are: manufacturers, suppliers, transporters, warehouses, wholesalers, retailers and other intermediaries [1].

In recent years, a variety of supply chain performance measurement (SCPM) systems have been published to quantify the efficiency and effectiveness of supply chain processes, their relationships and the multiple functions of organisations and companies to enable supply chain orchestration [3–6]. Companies can benchmark themselves against others through the use of supply chain maturity models. In both maturity models and SCPM, aspects related to environmental regulation are included in order to understand that natural resources are limited, so that companies adopt sustainable natural resource practices [7]. In addition to this environmental perspective, recent studies include company metrics from other perspectives that can influence their supply chain, such as: internal process, learning and growth, customer, social and financial [8]. On a financial perspective, neither the maturity models nor the supply chain improvement measurement models include an indicator of the economic sustainability of the company, such as the probability of company bankruptcy, to measure the continuity of the company and its influence on the supply chain.

Economic sustainability is important to pursue, as financial difficulties and failures of critical suppliers trigger announcements of supply chain disruptions that severely penalize

business operations [9–11]. Therefore, companies in a supply chain must maintain a healthy financial state to achieve the successful integration of their activities and proper coordination of all their key processes. Otherwise, the uncertainty and risks of bankruptcy of one company in the supply chain may threaten the operations and activities of the other companies in the supply chain [12].

Predicting the risk of bankruptcy is important for the early detection of signs of deteriorating financial conditions and can enable corrective action to be taken in the operation of the supply chain [13,14]. Consequently, companies with a stronger financial position can assume the liquidity necessary to maintaining their supply chain activity by accepting higher temporal payment terms or paying in advance to increase trade credit to companies with a weaker financial position and thus complement the financial health of these companies [15,16].

In this context, the research questions (RQ) considered in this investigation are two. RQ1: Which are the industries in the supply chains of Spanish companies with the highest probability of bankruptcy? RQ2: Which values allow the probability of bankruptcy to be delimited into three zones for the financial classification of a company?

In addition to the introduction, this article is divided into four sections. Initially, there is a review of the theoretical concept of the supply chain and the probability of bankruptcy, as well as Altman's bankruptcy Z-predictor. Then, the methodology of the study is presented. This is followed by the empirical study to answer the research questions. Finally, the discussion and conclusions of the study are presented, highlighting the supply chain industries with the highest probability of risk.

2. Theoretical Framework

2.1. Supply Chain

Supply chain management facilitates the flow of goods, information and money. Of these three elements, the least studied in the state of the art is the flow of money in the supply chain, which is called supply chain finance (SCF) [15].

Due to the increased dependency between companies in the ultimate supply chain, the bankruptcy of one company may cause other members of the chain to fall into financial difficulties [17].

The provision of liquidity to the supply chain helps to ensure its financial stability. The reduction of the cash conversion cycle increases the liquidity of companies in the supply chain, and therefore reduces the probability of bankruptcy of these companies [15]. The cash conversion cycle can be reduced by focusing on the optimization of working capital in terms of accounts payable, accounts receivable, inventions and sometimes even fixed asset financing [18]. The trade credit financing is another option to increase liquidity, which may increase the level of risk and bankruptcy, as it may stimulate more orders to be placed [19,20].

The ultimate supply chain, which includes service only supply chains (SOSCs) and the product service supply chains (PSSCs) [21], is different for each industry, so the causes of bankruptcy may vary for each industry [22].

At the industry level, the market demand, sales growth and sustainable growth of each company in the supply chain defines the company's strategic behaviour in various categories (expansive, dominant, shrinking, restructuring, in decline and unfocused) that can be used to predict companies' profitability [23].

The visibility of a supply chain and integration of suppliers to share information to detect the bankruptcy of a supplier in a supply chain enables risk management for intentional supply chain disruptions [24].

Therefore, the measurement of the probability of bankruptcy is important for the economic sustainability of each industry's supply chain. Since there is no such indicator in SCPM systems, there is a gap that is addressed in this research with a proposal to introduce a bankruptcy predictor and the analysis of bankruptcy in each industry.

2.2. Predictor of Bankruptcy: The Z-Score Model by Altman

A pioneering work of scientific research on the prediction of business failure dates back to the 1930s, when Fitzpatrick (1932) and Smith et al. (1935) applied a very basic univariate analysis based on the study of the evolution of financial ratios [25,26].

The contributions of Beaver (1966) incorporated a univariate discriminant analysis into the research with a separate evaluation of the predictive capacity of each one of the ratios considered, which meant a qualitative leap, although it was soon abandoned by multivariate techniques [27].

Altman (1968) was the pioneer in applying techniques of multivariate discriminant analysis (MDA) to the study of the prediction of corporate bankruptcy, replacing the previous contribution of Beaver [28]. With this research and others that followed, good results were achieved with minor classification errors [29].

Since then, this research line has been enriched by numerous contributions by different authors with new approaches and the incorporation of other techniques, such as artificial intelligence, neural networks, self-organized maps, multidimensional scales, and the Logit technique (which makes it possible to estimate the likelihood of failure for a set of constraints or attributes) [30–32].

Despite these other contributions, this Altman tool is commonly accepted to anticipate financial failures and bankruptcy risk in various industry sectors or companies within the same supply chain [33–35].

2.2.1. Altman Z-Score Model

The initial model was obtained in 1968 with a sample of 66 companies, of which 33 filed for bankruptcy and another 33 did not. All of the companies belonged to the US manufacturing sector, were medium-sized and were listed on the stock market for 20 years (1946–1965). The 66 financial statements were obtained from Moody's industrial manual, and from them Altman extracted 22 financial indices related to: profitability, indebtedness, activity, liquidity and solvency. He grouped these indicators into five variables, obtained from seven data from accounting and financial results [28], as can be seen in Table 1.

As a result of applying the multiple discrimination analysis technique to the sample of companies, Equation (1) was obtained:

$$Z = 1.2 X_1 + 1.4 X_2 + 3.3 X_3 + 0.6 X_4 + 1.0 X_5 \quad (1)$$

Companies in Edward Altman's sample that scored below 1.81 ended up in bankruptcy. While companies that scored above 2.99 were in a healthy financial zone. Consequently, those companies with scores between 1.81 and 2.99 were considered to be in the caution zone.

This model was criticized for being applicable only to capital-market-listed manufacturing companies and not to commercial and service companies, listed or unlisted. For this reason, Altman agreed to revise the model, although it is true that initially he resisted, arguing that it was not necessary. Finally, he published two new versions of the model, the Z' and the Z'' [36–38].

Despite this, recent academic articles can be found that still use this model instead of the latest update [39–42].

2.2.2. Altman Z' -Score Model

In 1983, an adjustment was made to the original model so that it could be applied to unlisted manufacturing companies. In particular, in the calculation of the X_4 ratio, it replaced the numerator with the book value of the equity instead of the market value of shares and divided by the book value of total liabilities [43]. Consequently, the new Equation (2) was obtained:

$$Z' = 0.717 X_1 + 0.847 X_2 + 3.107 X_3 + 0.42 X_4 + 0.998 X_5 \quad (2)$$

Table 1. Key figures of the initial Z-Altman model [28].

Variable	Name	Formula	Explanation
X_1	Liquidity ratio	$WCTA = \text{working capital} / \text{total assets}$	The part of the current assets that is financed using permanent resources is called the working capital. The relationship between the working capital and total assets is related to the capacity of a company to comply with its short-term financial obligations, that is to say, liquidity. Altman distinguished X_1 as one of the most important ratios, since it is proportional to the company's liquidity and therefore to its financial health.
X_2	Accumulated return ratio	$RETA = \text{accumulated reserves} / \text{total assets}$	The age of the company is quite relevant to predicting bankruptcy and insolvency, since a younger company is more likely not to survive compared to a company with an established operation or economic activity. Normally, older operating companies have a higher level of accumulated reserves. When the business accumulates losses, reserves may become negative. However, when it accumulates profits, the reserves will be positive, evidencing a capacity for growth and reinvestment to self-finance its projects.
X_3	Profitability ratio	$EBITTA = \text{profitability before tax and interest (EBIT)} / \text{total assets}$	If a company fails to consolidate its operation to generate sufficient resources, it will subsequently disappear from one year to the next because it is unable to meet its payment obligations. The higher the value of this variable, the lower the probability of bankruptcy.
X_4	Financial structure ratio	$BVETD = \text{market value} / \text{total liabilities}$	For quoted companies, the market value can be calculated using the stock market price. Its division into total liabilities allows it to be related to the book value. The result is a variable related to the financial structure. The higher the value of this variable, the lower the probability of bankruptcy of the company, since the market is valuing the company above its book value.
X_5	Asset turnover rate	$SALTA = \text{net sales} / \text{total assets}$	This indicator is associated with the speed of movement of assets, i.e., the administrative and commercial capacity of the company in relation to competition from other companies in the sector in which it operates. The result is interpreted as the number of times sales contain the asset.

In this model, results below 1.23 are considered likely to fail, while those above 2.99 are considered healthy. So, between 2.99 and 1.23 is a precautionary zone.

Altman did not validate this model with a second sample due to the lack of private companies in the database. He considered that the X_5 ratio (net sales/total assets) was influenced by the company's sector or industry, so he decided to make a new model valid for all industries or sectors, which he called the Z'' -score [37]. Nevertheless, in recent academic articles, this Z' model is likely to continue to be used instead of the latest update [9,44].

2.2.3. Altman Z'' -Score Model

In order to obtain a model suitable for use with all categories of companies, the variable X_5 from the above Equation (2) is excluded, since it is a value that varies significantly from one company to another in different sectors or industries, which causes a distortion and can influence the model. So, Equation (3) is obtained:

$$Z'' = 3.25 + 6.56 X_1 + 3.26 X_2 + 6.72 X_3 + 1.05 X_4 \quad (3)$$

In this other model Z'' , a firm with a score below 1.1 is considered a high bankruptcy likelihood, while if it is higher than 2.6, it is considered healthy. Thus, companies with a value between 2.6 and 1.1 are considered to be in a financial caution zone [36,37].

As before, instead of the latest update, recent academic articles can be found using this model [45–47].

2.2.4. Model Z-Score of Altman 2014

From the year 2000 to 2014 there have been published numerous scientific articles mentioning the Z-score Altman model. From a selection of 33 articles, 16 of them used the model to measure companies' financial strength or bankruptcy, 14 other studies verified and modified the model, and in 3 cases it was used to validate its robustness. Although this model has been published for many years and is widely accepted, it seems logical to think that it requires a revision, in which its parameters are re-estimated with more recent data and new estimation techniques are used.

For this reason, Altman and others have made a new version of Z-score model [43], with a new data sample of 2,640,778 companies (2,602,563 non-bankruptcy and 38,215 bankruptcy) from USA, China, Colombia and 31 European countries. New variables (country, industry, size and age) are also included and grouped into seven hypotheses to improve the performance of the model [48], which are shown in Table 2.

Table 2. The seven hypotheses considered by Altman in the updated model.

Hypothesis	Description
H1	Obsolescence of the coefficients. In the previous model, the same sample of companies was used as those in the initial Altman model carried out many years earlier.
H2	Estimation method. In the previous model, the method used for estimation is the MDA, which is based on the least squares method and requires the data to comply with the principles of multinormality, homoeasticity and linearity, which is not always possible.
H3	Bankruptcy year. Year in which the bankruptcy occurs. In contrast to the previous model, whose sample corresponds to a long period of time, specifically 1946–1965, the year is considered.
H4	Size of the company. The previous model did not include data from very small or very large companies.
H5	Age of the company. This is an additional contribution to previous model, since it does not explicitly consider the age of the company, even though it does influence the bankruptcy. Bankruptcy is more likely for young companies.
H6	Company sector or industry. The previous model was made for the productive industrial sector. The sector or industry influences the financial analysis and bankruptcy of companies [49].
H7	Country of origin. It allows the model to be adjusted to the country, since samples of companies from various countries have been used (USA, China, Colombia and 31 European countries)

Logistic regression expression was used to create this new Z-score model, since it does not require the data to comply with homoscedasticity, normality, and collinearity, which is required in previous Z-score models because they are obtained by MDA. The score of the new Z-score model is obtained with Equation (4), whose value represents the likelihood of failure, where the value 1 is the maximum and 0 the minimum.

$$Z = \frac{1}{1 + e^{-L}} \quad (4)$$

The value of the variable L in Equation (4) is obtained from a linear expression that depends on the hypotheses considered in the model. There are seven hypotheses, one for each model. Equation (5) represents the expression for the set of all the hypotheses at once, which has been called the eighth model of the Altman Z-score logistic regression.

$$\begin{aligned}
 L = & -13.302 - 0.459 X_1 - 1.160 X_2 - 1.682 X_3 - 0.013 X_4 - 0.034 D_1 \\
 & - 0.150 D_2 - 0.631 D_3 + 1.837 S_1 - 0.061 S_2 + 0.186 A_1 \\
 & - 0.099 A_2 - 0.628 I_1 + 0.365 I_2 - 0.157 I_3 - 0.176 I_4 \\
 & + 0.095 I_5 - 0.472 I_6 - 0.915 I_7 - 0.014 C_1
 \end{aligned} \quad (5)$$

The variables X_i in Equation (5) correspond to the Table 1. The dummy variable D_i refers to the latest year of available data in the accounting statement of the company, so that the values of D_i are, if the year is equal to or earlier than 2008 ($D_1 = 1$, $D_2 = 0$, $D_3 = 0$), if it is 2009 ($D_1 = 0$, $D_2 = 1$, $D_3 = 0$), and if it is equal to or greater than 2010 ($D_1 = 0$, $D_2 = 0$, $D_3 = 1$). The dummy variables I_i are zero unless the company corresponds to one of these industries: restaurants and hotels ($I_1 = 1$), building ($I_2 = 1$); wholesale and retailing ($I_3 = 1$); agriculture ($I_4 = 1$); manufacturing ($I_5 = 1$); energy and water production ($I_6 = 1$); or information technology ($I_7 = 1$). The dummy variable C_1 refers to the country risk of the company's home country and is based on Standard & Poor's country risk rating. This variable rates the payment risk of a country and implicitly assesses the economic situation of the country. Based on the S&P country risk value, the value of C_1 is: AAA = 1, AA+ = 2, AA = 3, AA- = 4, A+ = 5, A = 6, A- = 7, BBB+ = 8, BBB = 9, BBB- = 10, BB+ = 11, BB = 12, BB- = 13, B+ = 14, B = 15, B- = 16, CCC+ = 17, CCC = 18, CCC- = 19, CC = 20, C = 21, D = 22.

From the publication of the first Z-score model, 50 years have passed, and the Altman Z-score model has become a standard for estimating the probability of bankruptcy to enable analysis for credit granting, investments and mergers and acquisitions purposes [29].

A review of the academic literature indicates that the original model was developed for quoted companies, while the model Z' was focused on private manufacturing companies, and both models (Z'' and the Z-score 2014) were tailored to different companies (private and quoted) and different business purposes (manufacturing or non-manufacturing) [50].

The Altman model has been used in many academic papers. However, a review of the latest scientific papers reveals that some of the older Z-score models are used, rather than the latest version which is more complete and updated. It is uncertain why the scientific community continues to use an older model, when the renewed model has been proven to be more accurate [51].

A possible explanation could be the industry typology of the companies in the study, but the latest Z-Score 2014 model, which is valid for all company typologies, should be used in any case. Another possible cause could be the lack of values that allow the categorisation of the outcome of the probability of bankruptcy risk into several zones, as the previous models have. This is one of the contributions of this article.

3. Methodology

The methodology consists of a statistical study of the latest version of the Altman bankruptcy predictor on a dataset of Spanish firms from different industries over a period of time.

The sample of dataset is based on 1379 Spanish companies (73% are public limited companies and 27% are limited liability companies) that have accounting data for the annual period between 2010 and 2013. The data for this sample have been obtained from the SABI (Iberian Balance Sheet Analysis System) database.

The SABI database has classified the main activity of the companies according to the Spanish National Classification of Economic Activities (CNAE 2009). In order to apply the Z-Score model [43], the classification of this model must be used, so an equivalence has been made between both codifications. Table 3 shows this equivalence between the CNAE

2009 classification and the Z-score. This equivalence is simple, since there is an almost univocal equivalence between both codifications. Thus, the companies in the study are grouped into seven main industries, and the remaining companies are grouped into the “others” category.

Table 3. Table of equivalences of economic activities between CNAE and Z-score Altman 2014. Source: own elaboration.

CNAE 2009		Z-Score Altman 2014 [43]	
I	Restaurants and hotels	1	Restaurants and hotels
F	Building	2	Building
G	Wholesale and retailing	3	Wholesale and retailing
A	Agriculture, farming, forestry and fishing	4	Agriculture
C	Manufacturing industry	5	Manufacturer
D, E	Supply of electricity, gas, steam and air conditioning; water supply, sanitation, waste management and decontamination activities	6	Energy and water
J	Information and communications	7	Information Technology
B, H, K, L, M, N, O, P, Q, R, S, T, U	Extractive industries; financial and insurance activities; real estate activities; professional, scientific and technical activities; administrative and support service activities; public administration and defence; compulsory social security; education; human health and social work activities; arts, entertainment and recreation; service activities; activities of households as employers of domestic personnel; activities of households as producers of goods and services for own use; activities of extraterritorial organisations and bodies	8	Others

4. Empirical Study of the Eighth Model of the Altman Z-Score Logistic Regression

In total there is a large sample of data, consisting of 5516 financial statements of Spanish companies from different industries on which the calculations have been performed to obtain the values for the Z''-score model [36,37] and the eighth model of the Altman Z-score [43].

The bankruptcy financial classification of the companies according to the Z'' version has been used to obtain the values of the companies for each of the classifications with the eighth model of the Altman Z-Score Logistic Regression. The results of these calculations are contained in Table 4.

Table 4. Table of the descriptive values of the eighth-model of the Altman Z-Score Logistic Regression of the research sample based on the bankruptcy financial classification of Z''-score model. Source: own elaboration.

Financial Classification of the Company Z''-Score Model [36,37]	N	Average	Standard		The 95% Confidence		Min.	Max.
			Deviation	Error	Interval for the Mean Lower	Upper		
Likely bankruptcy	100	0.315033	0.1340710	0.0134071	0.288431	0.341636	0.0833	0.5865
Caution	419	0.274204	0.1140356	0.0055710	0.263254	0.285155	0.0583	0.5665
Healthy	4997	0.222384	0.1051514	0.0014875	0.219468	0.225300	0.0020	0.5958
Total	5516	0.228000	0.1079477	0.0014535	0.225151	0.230849	0.0020	0.5958

The average values of the probability of bankruptcy, according to the latest Z score of each grouping of financial statements of the companies, have allowed us to obtain the boundaries of each of the three categories (likely bankruptcy, caution and healthy) that have allowed us to answer the research question RQ2.

Table 5 shows the summary obtained, which establishes the equivalence of the groupings for both bankruptcy models. Although the probability of bankruptcy's value ranges from 0 to 1, a company enters the probability of bankruptcy category from a low value of 0.315 onwards.

Table 5. Equivalence of the financial classification between the Z''-Score model and the renewed measurement of the eighth model of the Altman Z-Score. Source: own elaboration.

Financial Classification of the Company	Z''-Score [36,37]	The Eighth Model of the Altman Z-Score [43]
Healthy	$2.6 < Z''\text{-score}$	$0 \leq Z\text{-score} < 0.2223$
Caution	$1.1 \leq Z''\text{-score} \leq 2.6$	$0.2223 \leq Z\text{-score} \leq 0.3150$
Likely bankruptcy	$Z''\text{-score} < 1.1$	$0.3150 < Z\text{-score} < 1$

The statistical results of the eighth model of the Altman Z-Score Logistic Regression are shown in Table 6. This table is ordered from the lowest to highest probability of failure for each industry in order to answer research question RQ1.

Table 6. Measurement of the eighth model of the Altman Z-score for different industries. Source: own elaboration.

Industries	N	Average	Standard		95% of the Confidence		Min.	Max.
			Deviation	Error	Interval for the Mean Lower	Upper		
Information technology	236	0.14	0.06	0.00	0.13	0.14	0.02	0.33
Restaurants and hotels	124	0.18	0.07	0.01	0.17	0.20	0.08	0.42
Agriculture	56	0.20	0.06	0.01	0.18	0.21	0.11	0.39
Wholesale and retailing	1344	0.21	0.09	0.00	0.21	0.22	0.05	0.47
Energy and water	176	0.25	0.07	0.00	0.24	0.26	0.10	0.39
Manufacturer	2376	0.27	0.09	0.00	0.27	0.27	0.06	0.59
Building	316	0.37	0.10	0.01	0.36	0.38	0.10	0.60
Others	888	0.12	0.05	0.00	0.11	0.12	0.00	0.31
Total	5516	0.23	0.11	0.00	0.23	0.23	0.00	0.60

Companies in the construction industry supply chain have the highest probability of bankruptcy, which is in the probable bankruptcy category. Next, the manufacturing and energy and water industries are in the financial caution category. Then, in the healthy category, according to the probability of risk, are the following industries: wholesale and retailing, agriculture, restaurant and hotels and information technology industries, respectively.

The grouping of industries categorized as others has the lowest probability of bankruptcy of all.

A comparison of the maximum values for each industry shows that the ranking remains the same, although it can be concluded that within each industry there is a deviation close to the value 0.1, which means that there are very different financial situations for each one.

5. Discussion

This study introduces the convenience of including a new indicator for measuring the performance of the supply chain (SCPM) to assess the probability of company bankruptcy. These SCPM indicators can be shared among supply chain companies to improve supply chain operations and allow for a more efficient supply chain. In addition, significant differences in the probability of bankruptcy have been found for each of the industries.

The information technology industry's supply chain is comprised of technology services that are experiencing rapid progress in cloud computing to reduce costs, as well as technology products that enable end customers to gain cost efficiencies in their information flows [52,53]. This increased efficiency for the ultimate customer could be leading to greater liquidity and financial credit for companies in this industry, which reduces the likelihood of company bankruptcy and the disruption of the company's industry supply chain.

The restaurant and hotel industry supply chain is related to the economic power of the final consumers and the economic activity of other industries [54,55]. Due to the fact that the data corresponds to a growth economic moment, after the crisis of 2008, that enhanced the efficiency of the companies in the industry, which justifies the healthy situation in Table 6.

In the agricultural industry, the supply chain has been found to have more stable relationships over time, which have positive effects on chain upgrading that justify a healthy probability of bankruptcy [56–58].

The wholesale and retail supply chain has high cash requirements and therefore financial risk, and can be protected by insurance and mechanisms to enhance financial decisions with commercial and bank credits. So, an increase in bank lending rates is an indicator of the reducing the profits of these companies. The period of years of the sample of companies corresponds to low interest rates, which improves the profits of this industry and provides it with a healthy financial situation [59,60].

The energy and water supply chain involves high investment in infrastructure regulated by the country's government, requiring constant adaptations and changes in regulations that require additional capital investment. The increased investment, and the lack of updated government-regulated prices for these companies caused the margins of companies in this industry to shrink sharply. Therefore, the probability of bankruptcy increased, which caused this industry to be in the caution zone [61–63].

The manufacturing industry is composed of supply chains that have to be particularly attentive to risks in operations, as this influences the efficiency of the supply chain and potentially poses risks. Therefore, besides the product, the quality of the information and service must be improved to reduce the supply risk and avoid the likelihood of bankruptcy. This need to manage supply risk caused the industry to be in a cautionary zone [64,65].

The building industry's supply chain has numerous risks, which if not properly managed can contribute to an increased probability of bankruptcy. Moreover, managers in this industry try to use their expertise rather than analytical tools to reduce risk. The industry's specific characteristics, such as the culture and fragmentation of its supply chains, among others, have led to a reluctance to improve and reduce the complexity of supply chain management. As a result, the industry was in the zone of probable bankruptcy [66–68].

Consequently, the new indicator for SCPM recommended as a predictor is the Altman Z-score, which, despite being simple, has been shown to be capable of reliably predicting businesses' failure or bankruptcy and is currently being used by investors [69–72].

The previous Altman models (Z , Z' and Z'') were based on the multi-parameter multiple discriminant analysis (MDA) method. This method requires that the independent

variables of the parameters satisfy some requirements (normality, linearity, homoscedasticity), which are not fulfilled for the financial variables used.

The logistic or logit regression technique has been applied to the renewed Altman model [43], eliminating the limitation of the MDA models, which require that the data satisfy homoscedasticity, normality, and collinearity. Additionally, new variables have been considered that provide a more accurate model [43,73]. Despite this, academic publications are more likely to use the earlier versions of Altman, as they are more familiar and easier to use.

The new revision of Altman's Z-score model is considered to have some parameters that are already outdated. For example, a dummy variable refers to the last year with data available from the accounting status of the company, and is only referenced for the years 2007 to 2010, so if a study is made at present this variable will be zero for all companies, since many of them will have accounting statements for 2010 unless they were newly created. In the same way, the variable for considering the company's country of origin is supported by Standard & Poor's country risk rating, but it has not been established what to do if this entity decides to introduce new ratings, as happened in the last crisis of 2008.

The introduction into the Altman's 2014 Z-score model of a variable reflecting the age of the company and another variable reflecting the country risk is considered positive, as it overcomes the myopia of discriminatory methods on the time and macroeconomic axes.

This research is one of the earliest to apply Altman's 2014 Z-score model 8 [43], to perform a ranking of the probability of bankruptcy for supply chain firms of different industries. Furthermore, this study provides for the first time a ranking of the financial probability of bankruptcy of companies for this new z-score model.

The main limitations of this study are that it was conducted for Spanish companies during a period of time after the 2008 crisis.

6. Conclusions

This article fills the gap in the financial perspective of supply chain improvement performance measurement (SCPM), related to the lack of a bankruptcy predictor, which allows the company to summarize the probability of bankruptcy and compare itself with other companies in its industry and in the supply chain sector of this company. For SCPM, the inclusion of an indicator to predict the probability of bankruptcy of the company, such as the eighth model of the Altman Z-score, is recommended.

In addition, a ranking of the bankruptcy probability by industry has been established, based on a study of a large sample of financial statements of Spanish companies, which allows us to answer research question RQ1. This ranking can be used to benchmark companies in an industry's supply chain, since it can be compared with the average value obtained for the probability of bankruptcy for each case. A very large empirical sample of Spanish firms has been used, which has allowed for greater precision in the results obtained.

Furthermore, this paper is a pioneer in the classification of firms into three categories (healthy, cautious and likely bankruptcy) for the prediction of financial distress using Altman's new Z-score model, which has answered research question RQ2.

Future studies can be suggested, such as the analysis of the evolution of the companies studied and which ones became bankrupt after 2014. Similarly, the strategic behaviour of each company can be reviewed to determine the influence of the company's bankruptcy on the supply chain of the industry to which it belongs.

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