BUSINESS BANKRUPTCY PREDICTION MODELS: APPLICATION TO COMPANIES IN THE CONSTRUCTION SECTOR IN SPAIN

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Abstract

In recent years, many authors have developed different models with the aim of predicting corporate insolvency, but none of them has proved irrefutable.

The construction sector was one of the most affected in Spain during the economic crisis of 2008, which caused the close down of a multitude of companies. Throughout this thesis, the most relevant bankruptcy prediction models have been applied, and subsequently studied how these models work in companies of the construction sector in Spain.

Moreover, two models created from the statistical software SPSS and Minitab have been proposed. Subsequently, the predictive capacity of these models when applied to Spanish construction companies have been analysed, comparing their accuracy with the models previously applied.

In the particular case of the construction sector in Spain, both proposed models far exceed the predictive ability of the most relevant bankruptcy prediction models applied; the most suitable being the one created with SPSS.
Keywords: Insolvency, prediction models, construction sector, Spain

In den vergangenen Jahren haben viele Autoren unterschiedliche Modelle mit dem Ziel, die Insolvenz von Unternehmen vorhersagen zu können, entwickelt, aber keines von ihnen hat sich als unwiderlegbar erwiesen.

Der Bausektor war einer der am stärksten betroffenen in Spanien während der Wirtschaftskrise von 2008, die die Schließung einer Vielzahl von Unternehmen verursachte. In folgender Dissertation wurden die wichtigsten Konkursvorhersagemodelle angewandt und danach wurde untersucht, wie diese Modelle in Unternehmen des Bausektors in Spanien funktionieren.

Darüber hinaus wurden zwei Modelle, die mit den statistischen Softwares SPSS und Minitab erstellt wurden, vorgeschlagen. Anschließend wurde die prädiktive Fähigkeit dieser Modelle, bei der Anwendung auf spanische Baufirmen, analysiert und deren Genauigkeit mit den bisher angewandten Modellen verglichen.

Im Einzelfall des Bausektors in Spanien übersteigt die prädiktive Fähigkeit beider vorgeschlagenen Modelle im Vergleich zu den wichtigsten Konkursvorhersagemodellen bei Weitem. Insbesonders das Modell erstellt mit SPSS.
Schlüsselwörter: Insolvenz, Vorhersagemodelle, Bausektor, Spanien

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List of abbreviations

BOE	*Boletín Oficial del Estado* (Official State Gazette)
CNAE	*Clasificación Nacional de Actividades Económicas* (National Classification of Economic Activities)
df	Degrees of freedom
EBIT	Earnings Before Interest and Taxes
EBITDA	Earnings Before Interest, Taxes, Depreciation, and Amortization
ECB	European Central Bank
FFO	Funds From Operations
FI	Financial Investments
FMI	Fails Management Institute
GDP	Gross Domestic Product
GNP	Gross National Product
IBM	International Business Machines
INE	*Instituto Nacional de Estadística* (National Statistics Institute)
MBTI	Myers-Briggs Type Indicator
MDA	Multiple Discriminant Analysis
NI	Net Income
ROA	Return On Assets
ROC	Return on Capital
ROE	Return On Equity
SA	*Sociedad Anónima* (public limited company)
SABI	*Sistema de Análisis de Balances Ibéricos*
SAU	*Sociedad Anónima Unipersonal* (sole proprietorship public limited company)
SL	*Sociedad Limitada* (private limited company)
SLU	*Sociedad Limitada Unipersonal* (sole proprietorship private limited company)
SPSS	Statistical Package for the Social Sciences
TEA	Temporary Employ Agencies
US	United States

1. Introduction

The construction sector was one of the most affected in Spain during the economic crisis of 2008. Specifically, 14,764 companies in this sector were insolvent in the period from 2007 to 2016 (Instituto Nacional de Estadísitca (INE), 2017) (in English, National Statistics Institute).

Despite the bankruptcy of Lehman Brothers in September 2008 was motivated by subprime mortgages in the United States, the problem in the Spanish economy was not only the losses of valuation of financial assets derived from subprime mortgages but also the excesses during the boom years: abundance of sources of liquidity, very low-interest rates, etc. These conditions created an environment in which the requirements for granting credit were exceptionally lax. Under these circumstances, the construction sector became the main destination for bank financing and the main source of income for credit institutions (Zurita, 2014).

This was one of the worst global financial crises and it had a devastating impact, causing the closing down of a multitude of companies, the paralysis of private consumption and the destruction of employment. The latter was mainly based on the construction, which encouraged to stimulate private indebtedness and real estate speculation. During the period from 1995 to 2007 Spain experienced an unprecedented growth in real estate activity, leading to over-dimensioning of the related sectors, which are still suffering the effects of the crisis.

The outbreak of the international financial crisis revealed weaknesses in the Spanish financial sector, since when the real estate sector showed symptoms of oversaturation, sales plummeted, and this effect was transmitted to other sectors of the industry that depended on it. As a consequence, the rest of the sectors of the national economy were impacted.

1.1. Thesis purpose

In the past several years, many authors have developed different models based on financial ratios with the aim of predicting corporate insolvency. The aim of this thesis is to study the applicability of these models in companies of the construction sector in Spain, being the first research question how can these models, intended to predict business insolvency, work for these companies. Therefore, an empirical analysis will be carried out, studying the accuracy of the models and the way they work in bankrupt and non-bankrupt companies.

The second research question is whether there is a new model that is more applicable to the reality of companies in the construction sector in Spain. Therefore, in addition to the study of existing models, a specific model will be proposed, analysing its effectiveness in contrast to the previously applied models.

1.2. The insolvency concept

Before proceeding with the purpose described above, it is necessary to define the concept of insolvency, and firstly it is essential to differentiate between insolvency and bankruptcy.

While insolvency is a financial condition such that the sum of the debts of an entity or a particular is greater than its property, at fair value (U.S. Code, 1978), bankruptcy is a legal status of a person or an entity that cannot repay the debts it owes to creditors.

There are also two kinds of legal bankruptcy under U.S. Law: involuntary, when one or more creditors petition to have a debtor judged insolvent by a court; and voluntary, when the debtor brings the petition. In both cases, the objective is an orderly and equitable settlement of obligations (Downes & Goodman, 2010).

This thesis will focus on the bankruptcy concept, considering as bankrupt companies those declared in insolvency proceedings in Spain.

1.3. Thesis structure

Regarding the structure of the thesis, firstly the Spanish economic situation, and in particular the one of the construction sector, will be analysed through variables such as GDP or the number of companies in the period from 2008 to 2016. An analysis of the financial information of the construction sector will also be carried out in order to understand the most characteristic aspects of the sector.

Secondly, a theoretical review of the insolvency prediction models will be carried out, discussing the different methods and the most outstanding authors of each of them.

Thirdly, a sample with solvent and insolvent companies will be selected and the most relevant models will be applied to it, assessing their effectiveness and the way they are applicable to companies included in the chosen sector.

Then, from the reviewed literature and the analysis of the sector carried out, two models to predict business failure of Spanish construction companies will be created through two different statistical software: SPSS and Minitab. These models will be compared with those relevant models previously applied, to determine to what extent are more suitable.

Finally, the non-financial factors that influence the insolvency situation of the construction companies will be analysed. Since although non-financial factors are more complicated to analyse than the financial ones, they are essential for the survival of the companies.

2. The construction sector in Spain

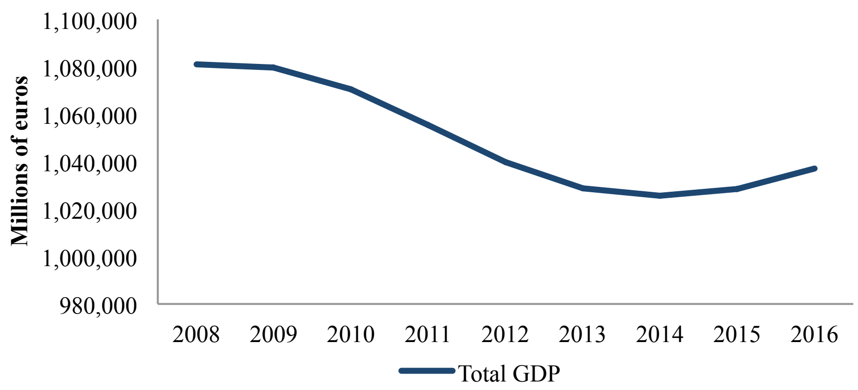
In this section, the economic situation in Spain, and in particular the situation of the construction sector, will be briefly analysed through variables such as the Gross Domestic Product or the number of companies. In addition, the most significant financial aspects of the Spanish construction sector will be studied.

2.1. Economic situation in Spain

Spain is currently recovering from the period of the economic recession of 2008, which has notably affected the national economy, causing the close down of many companies.

To illustrate the effects of the crisis, Figure 1 shows the evolution of Spanish Gross Domestic Product (GDP) in the period from 2008 to 2016.
From 2008 GDP experienced a drastic fall, from 1,080,913 million euros in 2008 to a value of 1,025,634 million euros in 2014. However, from 2015 the total GDP increased, reaching the volume of 1,037,025 million euros in 2016, demonstrating an incipient recovery of the Spanish economy.

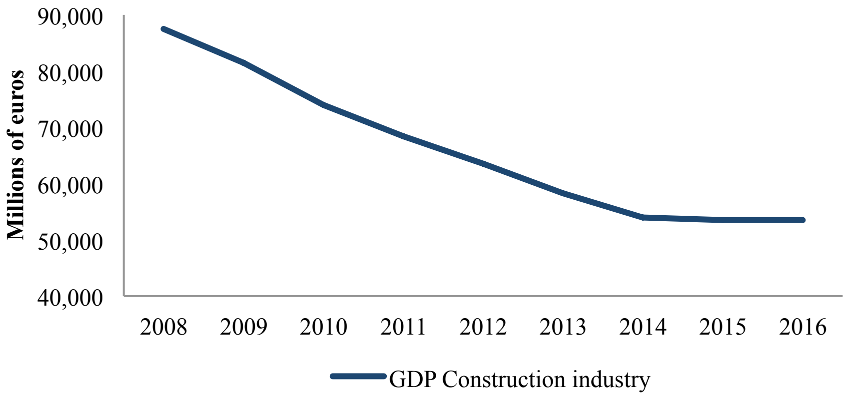
Figure 1. Evolution of the GDP in Spain (2008-2016)



Source: Own elaboration based on data from (Instituto Nacional de Estadísitca (INE), 2017)

In the case of the construction sector GDP (Figure 2), it sustains a sharp reduction between the years 2008 and 2014; going from 87,526 to 53,948 million euros, meaning a reduction of 38.36%. This shows faithfully the tragic effects of the crisis on this particular sector. Although like the Spanish GDP, the construction sector GDP is also reduced during the last two years of the analysed period, it decreases in a less drastic way, reaching a value of 53,524 million euros in 2016.

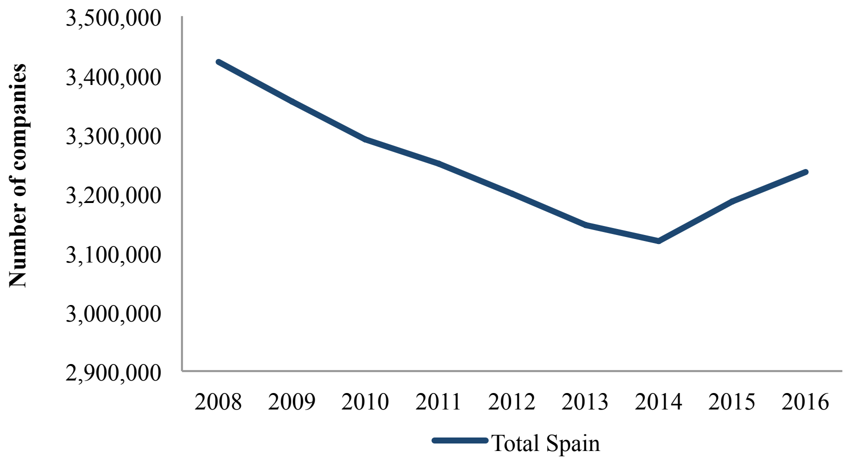
Figure 2. Evolution of the construction sector GDP in Spain (2008-2016)



Source: Own elaboration based on data from (Instituto Nacional de Estadísitca (INE), 2017)

As Figure 3 shows, the number of companies in Spain declined considerably in the period from 2008 to 2014, going from 3.42 to 3.11 million (approximately a reduction of 9%). Nevertheless, from the year 2014, an incipient recovery can be observed, increasing the number of companies up to 3.23 million in 2016.

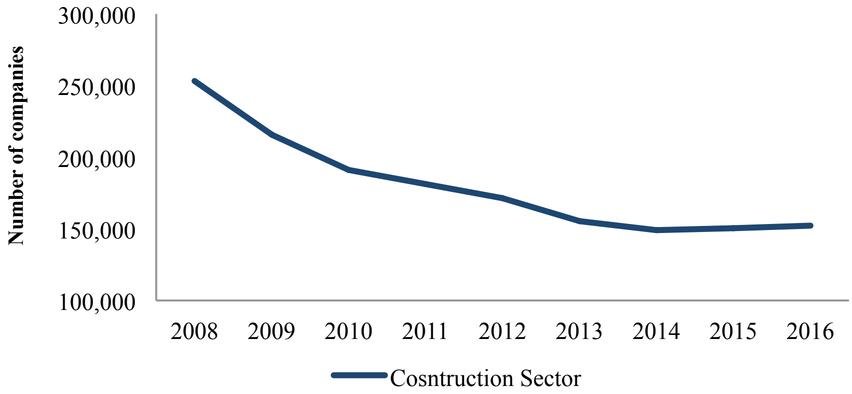
Figure 3. Evolution of the number of companies in Spain (2008-2016)



Source: Own elaboration based on data from (Instituto Nacional de Estadísitca (INE), 2017)

Figure 4 displays the evolution of the number of construction companies in Spain. The number of companies has followed a constant decrease in the analysed period, going from 253,188 companies in 2008 to 152,089 companies in 2016, which means a reduction of approximately 40%; demonstrating the devastating effect of the crisis.

Figure 4. Evolution of the number of companies within the construction sector in Spain (2008-2016)



Source: Own elaboration based on data from (Instituto Nacional de Estadísitca (INE), 2017)

Likewise, according to data from *Instituto Nacional de Estadística*, the number of companies declaring insolvent in Spain increased noticeably in the analysed period, rising from 2,894 in 2008 to 9,143 companies in 2013, an increase of almost 216%. It should be noted that since that moment they diminished gradually until 4,080 in 2016 (a decrease of 55%).

In the particular case of the construction sector, the bankrupt companies rose from 286 to 854 in the period from 2008 to 2012 (an increase of approximately 199%), decreasing from that point to 238 companies in 2016, which means a reduction of around 72% from 2012 (Instituto Nacional de Estadísitca (INE), 2017).

2.2. Financial analysis of the construction sector in Spain

This thesis aims to determine the effectiveness of models that can predict if a company is likely to be in a state of business insolvency, applied to companies in the construction sector in Spain. For this purpose, it is essential to understand the financial structure of this sector.

In this section, the financial information of the Spanish construction sector will be analysed with the intention of understanding which aspects are the most significant. In this way, it will be possible to determine to what extent the predictive models of insolvency consider these aspects. To this end, the financial information of the construction sector will be compared with the industry sector.

The data corresponding to the balance sheet and the profit and loss account of both sectors will be obtained using the “Central de Balances” (Central Balance Sheet Data office) tool from the *Banco de España* webpage.

In particular, the analysed financial statements are those for the period from 2005 to 2015; a wide period has been selected to see to which extent the sector has modified its financial structure, according to the aspects mentioned above.
It should be noted that the information for the year 2016 has not been included because it is not yet available.

Before beginning the financial analysis, it is necessary to take into account several limitations (Amat i Salas, 2008):

- The analysis is based on historical data, so there is sometimes insufficient understanding of where the company is going.

- The companies data is recorded at year-end, which normally is at December 31 of each year. In many companies, the situation is significantly different at the end of the year, since there may be seasonality in sales, production, expenses, collections or payments.

- Sometimes the companies manipulate the accounting data, which may then not reflect reality.

- The accounting information is not usually adjusted for inflation, so items such as inventories, fixed assets, or depreciation, may be inaccurate.

The analysis will be structured in the following sections: balance sheet structure, profit and loss account structure, liquidity analysis, leverage analysis, profitability analysis, and activity analysis.

It must be considered that the analysis of financial ratios will be based on the ratios that most faithfully reflect the situation of the sector.

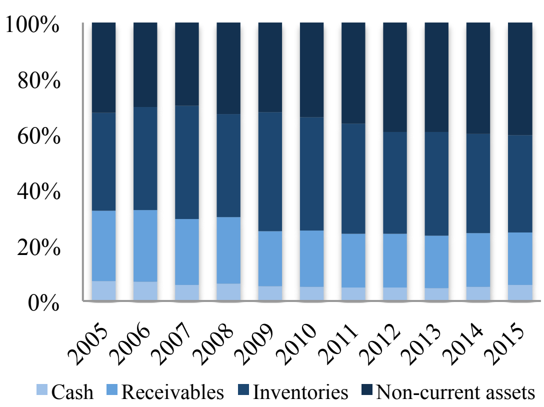
Appendix 1.A and **Appendix 1.B** show the financial information for the period 2005-2015 of the construction sector and of the industrial sector, respectively, and **Appendix 2.A** and **Appendix 2.B** the ratios calculated for both (Banco de España, 2016).

2.2.1. Balance sheet structure analysis

In this section, the balance sheet structure of the construction sector and the industrial sector will be studied. For this purpose, the analysis will be divided into the analysis of the assets side, and the analysis of the equity and liabilities side.

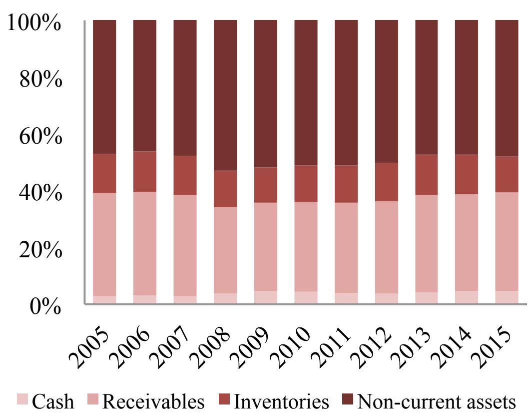
In order to make the analysis more visual, Figure 5 and Figure 6 show how the assets side of the construction sector and the industrial sector are composed, respectively:

Figure 5. Composition of the balance sheet of the construction sector, assets side (2005-2015)



Source: Own elaboration based on data from (Banco de España, 2016)

Figure 6. Composition of the balance sheet of the industrial sector, assets side (2005-2015)



Source: Own elaboration based on data from (Banco de España, 2016)

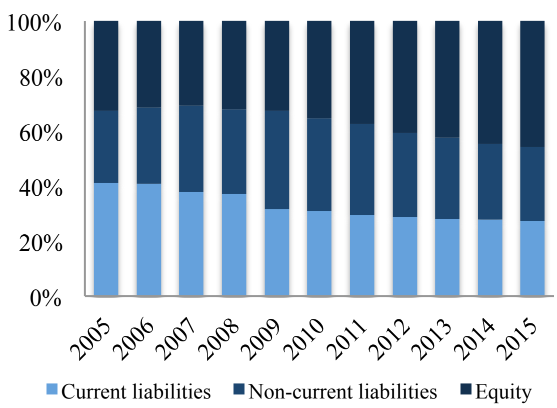
On the assets side of the balance sheet of the construction sector, the biggest item is current assets, in particular inventories, standing at around 39% of the total assets.

This makes sense given the sector's activity, which classifies the properties as inventories. Regarding non-current assets, which represent approximately 35% of the total, the heaviest balance sheet item is "Property, plant and equipment, and real estate investments".
In the industrial sector, non-current assets are the biggest item (49.13%) due to the high levels of property, plant and equipment, and the second biggest item is receivables, with 33.53% of the total assets.

It should be noted that the cash and cash equivalents are small both in the case of the construction sector and in the industrial sector, around 5% and 4%, respectively.

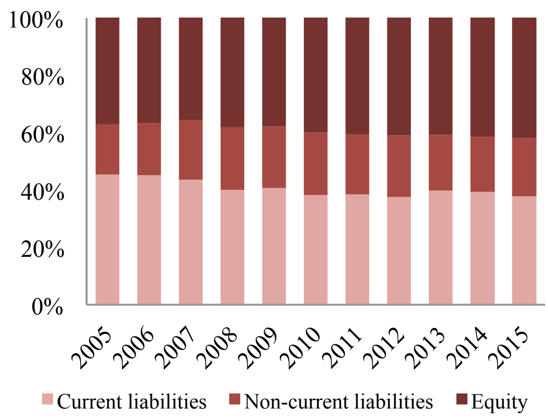
On the other hand, the composition of the equity and liabilities side of the construction and the industrial sector is the following:

Figure 7. Composition of the balance sheet of the construction sector, equity, and liabilities side (2005-2015)



Source: Own elaboration based on data from (Banco de España, 2016)

Figure 8. Composition of the balance sheet of the industrial sector, equity, and liabilities side (2005-2015)



Source: Own elaboration based on data from (Banco de España, 2016)

On the equity and liabilities side, in the construction sector, during the first years of the period analysed (from 2005 to 2008), the biggest item is current liabilities, representing around 39% of the total. Nevertheless, starting in 2009, the predominant item is equity, with approximately 41% of the total.
With respect to the industry sector, from 2005 to 2009 the largest item is also current liabilities (around 43%), and as of 2010, the heaviest item is equity, which represents

about 41% of the total.

This change in the structure of the equity and liabilities side of the balance sheet in both sectors is not due to a decrease in short-term debt but to an increase in equity. Moreover, it should be mentioned that this increase in equity is not motivated by an increment in the net income but by an increase in reserves.

2.2.2. Profit and loss account structure analysis

To analyse the structure of the profit and loss accounts, the contribution of each item to revenues has been calculated (**Appendix 3.A** for the construction sector and **Appendix 3.B** for the industrial sector).

Fist, it is necessary to study the evolution of the construction sector's revenue, which has suffered a significant deterioration in the analysed period, decreasing by 69% between 2005 and 2015 (from 37,991,586 to 11,615,097 thousand euros). This decrease is explained by factors like reduction in demand, debt collection problems of accounts receivable, and decrease in funding sources, among others.
For its part, the industrial sector's revenue is slightly reduced (-7%) in the analysed period.

Secondly, the gross margin**,** which can be defined as net sales less the cost of goods sold, will be analysed. In the construction sector, the gross margin remains around 95% of the revenue in spite of a reduction of 70%. For its part, the gross margin of the industrial sector is reduced by 13% in the analysed period and represents around 90% of the revenue at the end of the period.

In terms of expenses, the "other operating expenses" stand out in both cases. In the construction sector, despite declining in absolute numbers, these expenses are high throughout the period, going from 67% to 62% of revenue. With respect to the industrial sector, other operating expenses go from 75% of the revenue in 2005 to 71.5% of the revenue in 2015.

Finally, regarding the profit or loss of the period, it suffered a great deterioration in the period from 2005 to 2015, both in the construction and industrial sector.
In the construction companies, profit or loss of the period decreased by around 102% (from 1,801,864 thousand euros in 2005 to –42,972 thousand euros in 2015). On the other hand, in the industrial sector, the reduction was approximately 33%.
It is important to mention that the profit or loss of the period of the construction sector registered negative values from 2009 onwards, as a result of the complicated situation faced by the sector.

2.2.3. Liquidity analysis

In this section, the liquidity situation of the construction sector will be studied, comparing their results with those of the industrial sector. In particular, the ratios considered and their calculation are the following:

$$\text{Current ratio} = \frac{\text{Current Assets}}{\text{Current Liabilities}}$$

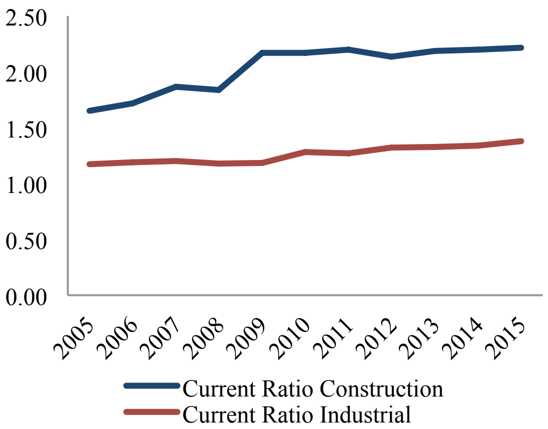
$$\text{Quick ratio} = \frac{\text{Cash equivalents } + \text{ Short term FI} + \text{ accounts receivables}}{\text{Current Liabilities}}$$

$$\text{Cash ratio} = \frac{\text{Cash equivalents } + \text{ Short term FI}}{\text{Current Liabilities}}$$

$$\text{Working capital to total assets ratio} = \frac{\text{Current Assets} - \text{Current Liabilities}}{\text{Total Assets}}$$

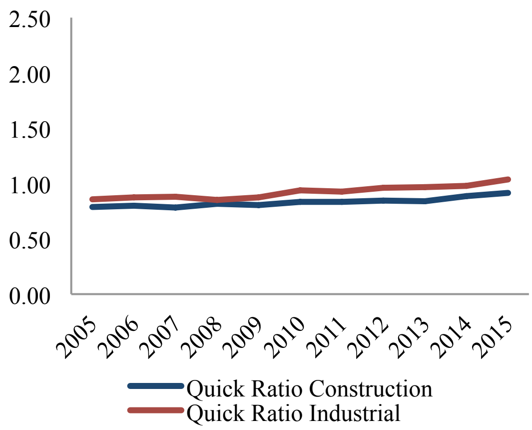
The results of the liquidity ratios and their analysis are the following:

Figure 9. Current ratio (2005-2015)



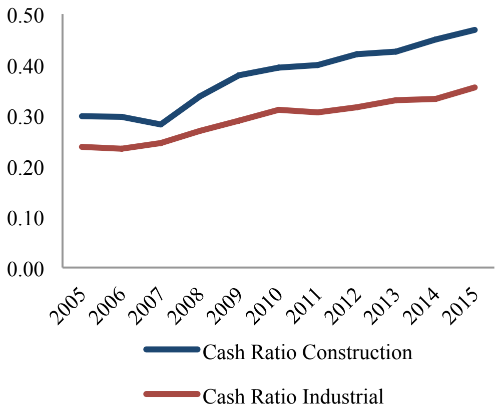
Source: Own elaboration based on data from (Banco de España, 2016)

Figure 10. Quick ratio (2005-2015)



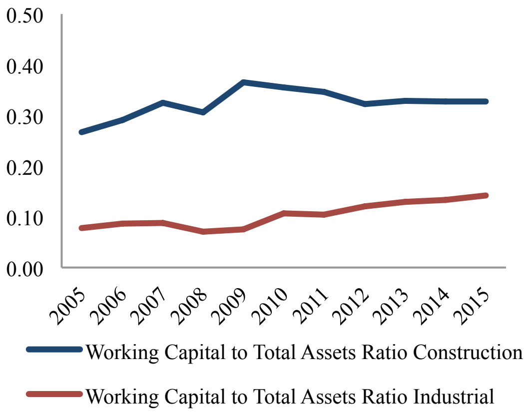
Source: Own elaboration based on data from (Banco de España, 2016)

Figure 11. Cash ratio (2005-2015)



Source: Own elaboration based on data from (Banco de España, 2016)

Figure 12. Working capital to total assets ratio (2005-2015)



Source: Own elaboration based on data from (Banco de España, 2016)

According to the current ratio (Figure 9), the liquidity situation of the construction sector has been optimal in the studied period. The ratio remained at values above of the unit, meaning the firms can easily meet their obligations in the short term. Regarding its evolution, the current ratio has maintained a marked increasing trend (from 1.65 in 2005 to 2.22 in 2015). For its part, the current ratio of the industrial sector takes lower values, around 1.26.

The quick ratio (Figure 10), which does not consider the stocks, shows a growing tendency (from 0.79 in 2005 to 0.89 in 2015). However, by eliminating the effect of stocks, the low values presented by construction companies can be appreciated. The ratio shows the inability of the companies to meet their more immediate obligations since it takes values lower than the unity. On the other hand, the quick ratio of the industrial sector stands around 0.92.

The cash ratio (Figure 11) measures a firm's ability to pay off its current liabilities with only cash and cash equivalents; consequently, it is much more restrictive than the current ratio or quick ratio. The companies in the construction sector only have enough cash and cash equivalents to pay off about 38% of their current liabilities. Although, the ratio presented a favourable evolution in the period studied, going from 0.30 in 2005 to 0.47 in 2015. For its part, the industrial sector registered values slightly lower than the construction sector (about 0.29).

The working capital to total assets ratio (Figure 12), measures a company’s ability to cover its short-term financial obligations. The ratio of the construction companies follows a slight increase during the analysed years, standing at around 32%. Since the ratio takes positive values, the construction sector has enough capital to run its day-to-day operations. Regarding the industrial sector, its ratio takes lower values than the construction sector (about 10.32%).

2.2.4. Leverage analysis

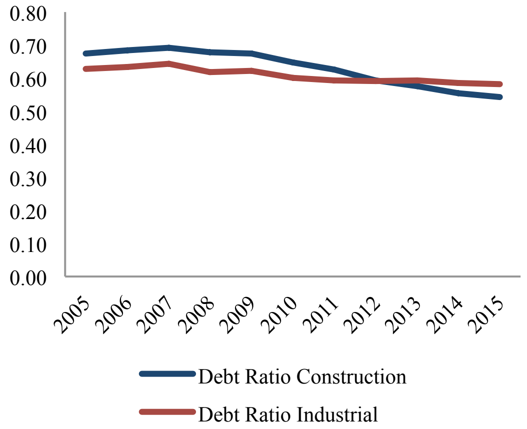
Concerning the leverage analysis of the construction sector, the studied ratios are the following:

$$\text{Debt ratio} = \frac{\text{Total Liabilities}}{\text{Total Equity and Liabilities}}$$

$$\text{Debt to equity ratio} = \frac{\text{Total Liabilities}}{\text{Equity}}$$

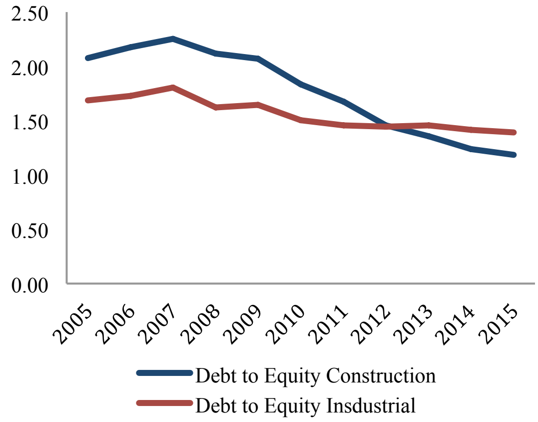
The results of the leverage ratios and their interpretation are the following:

Figure 13. Debt ratio (2005-2015)



Source: Own elaboration based on data from (Banco de España, 2016)

Figure 14. Debt to equity ratio (2005-2015)



Source: Own elaboration based on data from (Banco de España, 2016)

The debt ratio (

Figure 13) of the construction sector has taken relatively high values throughout the period (around 63%) with the maximum (69%) in 2007, due to the high level of short-term debt. Although, in the following years, the ratio decreased slightly, reaching a value of 54% in 2015. For its part, the debt ratio of the industrial sector takes similar values (about 61%).

The debt to equity ratio (Figure 14**)** shows the percentage of debt a company is using to finance its assets relative to the shareholders' equity. In the construction sector, the ratio stands around 177%, this means the sector is heavily indebted, thus has high risk. On the other hand, the debt to equity ratio of the industrial companies is close to that of the construction sector during the studied period (approximately 156%).

2.2.5. Profitability analysis

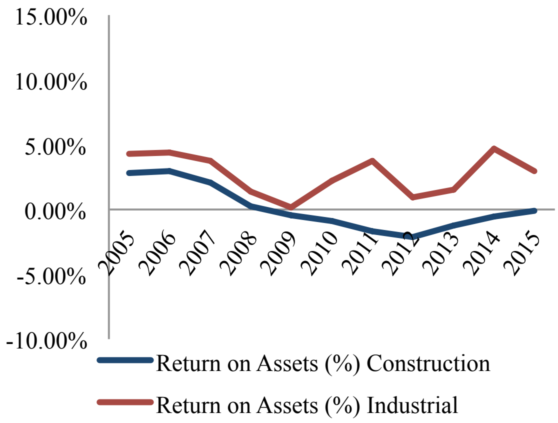
To carry out the analysis of the profitability of the sector, the following ratios have been used:

$$\text{Return On Assets (ROA)} = \frac{\text{Net Income}}{\text{Total Assets}}$$

$$\text{Return On Equity (ROE)} = \frac{\text{Net Income}}{\text{Equity}}$$

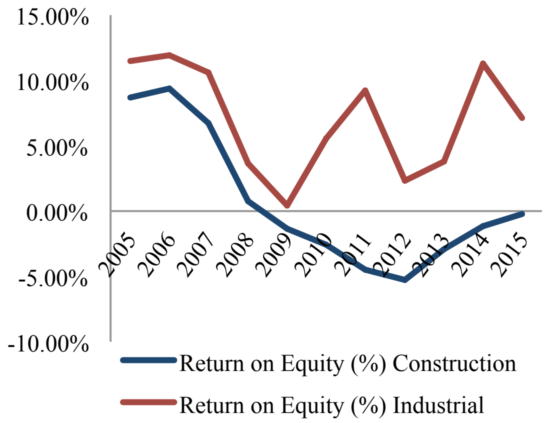
The results and analysis of the ratios above are:

Figure 15. Return on assets (2005-2015)



Source: Own elaboration based on data from (Banco de España, 2016)

Figure 16. Return on equity (2005-2015)



Source: Own elaboration based on data from (Banco de España, 2016)

Return On Assets (ROA) (Figure 15) measures the profitability of each euro invested in the company. The ROA of the construction sector undergoes a negative evolution in the analysed period, going from 2.82% in 2005 to -0.11% in 2015. It should be noted that the ROA of the construction sector shows negative values in seven of the years analysed (from 2009 to 2015) due to years' losses. Therefore, it can be concluded that the construction sector does not have optimal values (about 0.10% in average), considering that the ROA of the industrial sector is around 2.74%

Return On Equity (ROE) (Figure 16) is an indicator of shareholder's profitability or its opportunity cost. In the construction sector, the ROE follows a parallel evolution to the ROA, decreasing from 8.68% in 2005 to -0.23% in 2015. Moreover, it takes negative values from 2009 to 2015 due to the losses of the years, showing the complex financial situation of the construction sector. On the other hand, the ROE of the industrial sector takes more optimal values, around 7%.

2.2.6. Activity analysis

The ratios used in the business activity analysis are the following:

$$\text{Stock period (days)} = \frac{\text{Stocks} \times 365}{\text{Cosumption}}$$

$$\text{Average collection period (days)} = \frac{\text{Receivables} \times 365}{\text{Revenue}}$$

$$\text{Average payment period (days)} = \frac{\text{Payables} \times 365}{\text{Expenses and purchases}}$$

Where 365 is the total amount of days in the period.

The stock period is the number of days stock remain in the inventory. In the construction sector, the stock period takes absurdly high values due to the low value of consumption in relation to inventories, because inventories include real estate. Specifically, the stock period is around 8,265 days in the studied years. On the other hand, in the industrial sector, the stock period stands in values significantly lower, around 576 days. With respect to the evolution followed by the ratio, the stock period in the construction sector increased by 12% in the period from 2005 to 2015 due to the rise of stock. In the industrial sector, the stock period decreased by 61% in the analysed years.

The average collection period is the number of days a company takes to collect accounts receivable. In general, a lower average collection period is more favourable than a higher one, due to a low period indicates that the organization is collecting payment faster. In the construction sector, this ratio takes high values (around 145 days in average) and it follows an increasing trend (from 124 to 154 days in the period from 2005 to 2015), due to the decrease in revenue. On the other hand, the average collection period of the industrial sector is lower, standing around 92 days, what is more convenient.
It should be noted that his ratio is important because it measures liquidity indirectly. Many times can occur problems of delinquency, affecting the company’s ability to pay.

The average payment period is the average number of days the company takes to pay its creditors. In the period from 2005 to 2015, the ratio takes high values (around 277 days) due to the large debts of the construction sector. Regarding the average payment period of the industrial sector, it is about 127 days, a sign of a more convenient financial situation.

3. Business failure prediction models

The first empirical studies with the aim of predicting insolvency in companies were univariate analysis, being the study of W. H. Beaver (1966) one of the most widely recognized. Until that moment, insolvency prediction was in an embryonic state, using a single ratio, in particular, the current ratio, to diagnose insolvency. Beaver supported the use of different ratios and he applied t-tests to evaluate the importance of individual accounting ratios (Beaver, 1966). Nevertheless, these analyses were quickly replaced by a multivariate approach based on multiple discriminant analysis (MDA) where the model of E. I. Altman (1968) was the most commonly used.

However, the validity of the results of the MDA was soon questioned by the important statistical constraints characterizing this methodology. These constraints favoured the appearance of new studies based on conditional probability models, among which stand out the Logit and Probit models.

Should be noted that since Beaver’s study, the number of bankruptcy prediction models have increased dramatically, reaching 165 studies only until 2007 (Bellovary & Giacomino, 2007).

3.1. Multivariate discriminant analysis

Multivariate discriminant analysis (MDA) classifies firms in failed or non-failed based on each firm's characteristics (ratios). From sample observations, coefficients are calculated for each ratio and the products of the ratios and their coefficients are summed to give a discriminant score, allowing the classification of the firm.

The first multivariate discriminant analysis study was published by Altman (1968) and the popularity of this study remains to this day. Altman used the MDA to develop a five-factor model, called the “Z-Score” to predict manufacturing firms bankruptcy.
Specifically, Altman's Z-score model had a high predictive ability for the initial sample one year before failure (95% accuracy). However, the model's predictive ability dropped off considerably from there for the previous years before failure: 72% accuracy two years before failure and 48%, 29% and 36% accuracy for the third, fourth and fifth year before failure, respectively (Altman, 1968).

Although the Z-score model was extremely popular, there was a need to rebuild it because of the following reasons (Altman, Haldeman, & Narayanan, 1977):

1. The Z-score model was focused on relatively small firms and there was a dramatic increase in the average size of bankrupt companies at that time.

2. A new model that behave as up-to-date as possible regarding the temporal nature of the data was needed.

3. An updated model that was relevant for different industries (not only manufacturing but also retailers) was required.

4. The models seen up until that moment were only relevant for past failures. The new model had to be applicable to the data which would appear in the future as well.

5. An updated model able to test and assess several of the advances and controversial aspects of the discriminant analysis was required.

For the reasons exposed above, Altman et al. (1977) formulated the ZETA model, applicable to larger firms and not limited to specific industries. Besides that, the ZETA model demonstrated significantly improved accuracy over the last model, showing accuracy ranges from over 96% one year before the bankrupt and a 70% accuracy five reporting periods prior (Altman, Haldeman, & Narayanan, 1977).

There are two more adaptations of the ZETA model (Altman, 2000): Z' applicable to non-public traded companies and Z'' applicable to non-manufacturers, that show similar levels of accuracy that the ZETA model.

Nevertheless, although Altman's model is the most commonly applied, within the multivariate discriminant analysis is possible to find authors like Deakin (1972), Blum (1974) or Taffler (1983), among others (Bellovary & Giacomino, 2007).

However, despite the popularity of the multivariate analysis, it should be noted that the validity of the results of the MDA is conditioned by the statistical limitations of the technique used (Hair Jr., Black, Babin, & Anderson, 2009):

1. Multivariate analysis attributes a normal distribution to independent variables, nevertheless numerous studies show this is not usually the case (Deakin, 1976).

2. It implies the equality of the matrix of variances - covariances in the groups of failed and non-failed companies. Although some studies choose to work with quadratic models, most researchers try to avoid these models due to their excessive complexity and prefer a transformation of the data that approximates them to the fulfillment of this hypothesis in order to apply the linear model.

3. It does not consider the specific error in the initial classification. Numerous investigators do not to assign a priori the probability to the Type I error (misclassification of bankrupt firms as non-bankrupt) and the Type II error (non-bankrupt firms misclassified as bankrupt firms). Or if assigned, they consider it the same, but some studies show that Type I Error is much greater than Type II Error.
   An option to solve this problem could be to establish an interval in the value of Z, which defines the grey zone or zone of ignorance (Edmister, 1972).

3.2. Logit and Probit analyses

Early studies using the Logit and Probit analyses began to appear in the late 1970's, but they did not overtake MDA in popularity until the late 1980's. It should be mentioned that the main difference between the Logit and Probit analyses is that Probit one requires non-linear estimation (Dimitras, Zanakis, & Zopounidis, 1996).

Logit analysis is the most used, is less demanding than the MDA, and is not affected by the normality hypothesis nor by the equality of variance-covariance matrices. With this method, a linear relationship between the variables is assumed and the probability of business failure can be estimated. Its main limitations are (Tabachnick & Fidell, 2007):

1. Logit analysis assumes the dependent variable is dichotomous.

2. The cost of Type I and Type II errors should be considered in the definition of the optimum point in the Logit model. However, some authors do not recognize this limitation to be a serious problem.

3. Multicollinearity can be a thoughtful problem in this technique; since it is based on financial ratios that present a high correlation because they often coincide in the numerator or the denominator.

Within the Logit methodology, it is possible to find authors like Ohlson (1980), Zavgren (1983) or Pantalone and Platt (1987), among others (Bellovary & Giacomino, 2007).

The most commonly applied model within this methodology is that developed by Dr. James Ohlson. Ohlson postulated a financial formula, called O-Score, in 1980 as an alternative to the Altman Z-Score for predicting financial distress. The O-Score was derived from the study of a pool of over 2,000 companies, whereas its predecessor, the Altman Z-Score, considered just 66 companies. As a result, O-Score is an accurate predictor of bankruptcy, being its predictive ability greater than 96% one year before the bankrupt and 95% and 93% two and three years before the failure, respectively (Ohlson, 1980).

Within the Logit analysis, there are also specific models for the different sectors. In particular, in the construction sector can be found the models developed by Ihab Adel Ismail, among others.

In its 2014 research, Ismail developed a cash flow model to obtain the probability of failure of construction companies, validating the effectiveness of the model in predicting the failure 6 months, 1 year, and 2 years in advance of the bankruptcy at a statistically significant level. Ismail cash flow model describes a company's operational strength using a cash flow cycle with three measures: cash flow cycle profitability, cash flow cycle duration, and access to additional cash (Ismail, 2014).

The model developed by Ismail is based on cash flow due to, as Ismail affirms, the construction lifecycle could take as long as 60 days or more to complete the conversion into cash. Therefore, adequate sources of capital and a reasonable liabilities-to-assets ratio are critical factors for business continuity and success (Ismail, 2014).

4. Application of the models to the construction sector in Spain

In this section, some business failure prediction models will be applied to a sample of companies with the aim of determinate their effectiveness in the construction sector in Spain. For this purpose, the sample will be selected and the financial information of the companies that compose it will be obtained. Thereafter, the chosen insolvency prediction models will be applied to the sample. Finally, the accuracy of the models will be tested, comparing the accuracy of the applied models and analysing the variables used by each of them.

4.1. Sample collection

Before obtaining the sample of the Spanish companies within the construction sector, it is necessary to describe the population and to establish the size of the sample. Once the sample is chosen, the main parameters of the sample will be described.

4.1.1. Description of the population

The population will be divided into two different groups, solvent companies and insolvent companies.

To obtain the solvent companies, the database used was *Sistema de Análisis de Balances Ibéricos* (SABI). SABI is a database with general and financial information of two million Spanish companies and five hundred thousand Portuguese companies, obtained through official sources. This platform provides not only financial information but also indicates the number of employees, the last annual accounts deposited, if the company audits its annual accounts, among others.

SABI offers some searching options through different filters. In this case, the established filters were the following:

- About the economic sector, only companies included in the group *CNAE*[1] *412: Building construction* have been chosen. After applying this filter the number of companies obtained was 90,985.

- Subsequently, in order to carry out the most up-to-date work possible, those companies whose last accounts deposited correspond to the year 2015 or 2016 have been chosen.

- Finally, companies whose denomination includes the words insolvent or extinguished have been eliminated from the population.

[1] CNAE (Clasificación Nacional de Actividades Económicas), in English National Classification of Economic Activities, allows the classification and grouping of organizations according to the activity they perform (Ministerio de Economía y Hacienda, 2007).

After applying the filters mentioned above the number of solvent companies was 28,759 (Sistema de Análisis de Balances Ibéricos (SABI), 2017).

Regarding the insolvent companies, those declared in insolvency proceedings during the year 2016 will form the population. Although this information is not easy to obtain, there is a platform called *Gestión Integral Online de Concursos de Acreedores*, which collects all the companies in insolvency proceedings that the *Boletín Oficial del Estado* (BOE)[2] (Official State Gazette in English) publish every day.

This page has been the basis for the extraction of the population of insolvent companies. Of a total of 4,080 companies declared in insolvency proceedings in 2016, only those within the group *CNAE 412: Building construction,* have been chosen. After this process, the number of insolvent companies is 238 (Gestión Integral Online de Concursos de Acreedores, 2017), a very small number compared with the solvent companies obtained.

4.1.2. Establishment of sample size

To establish the sample size, in order to obtain an objective perspective, the formula below will be applied. It is important to mention that this formula is based on a calculation of the sample size for finite populations.

$$\text{Sample size} = \frac{\mathrm{N} \times \mathrm{p} \times \mathrm{q} \times \mathrm{K}^2}{\mathrm{e}^2(\mathrm{N}-1) + \mathrm{p} \times \mathrm{q} \times \mathrm{K}^2}$$

Where:

N: population size.
p: percentage of the population that has the studied characteristic.
q: 1 - p.
K: coefficient according to the confidence level of the results.
e: maximum permissible error for a confidence level.

[2] The BOE is the official Spanish Gazette dedicated to the publication of laws, provisions, and acts of mandatory insertion (Boletín Oficial del Estado (BOE), 2015).

In terms of the formula parameters, the population size (N) selected is 238. It should be noted that this number corresponds to the companies declared in insolvency proceedings. Since the number of solvent companies is greater than the number of insolvent ones, if the formula were applied with the former, it would not be feasible for the latter.

Concerning the parameters p and q, while p shows the common characteristics of the studied population, q shows those different aspects of the population. In this case, both variables are 0.5.

K is the equivalent to a coefficient associated with the level of confidence. A value of 1.96 has been chosen, corresponding to a confidence level of 95%.

Finally, the parameter e is equivalent to the maximum error to be assumed with regard to a given population (Moore, McCabe, & Craig, 2009). It has been considered that the maximum permissible error is 0.05, given a 95% confidence level.

The result obtained by applying the formula above is 147.19, that is, a total of 148 companies of each group should be selected.

4.1.3. Sample selection

To choose the sample, a random selection will be carried out in order to preserve an objective perspective. For this purpose, a macro, which generates random numbers randomly without repetition, has been created in Excel.

Subsequently, the financial data of the chosen companies was obtained through the SABI platform. It is necessary to emphasize that the obtained data was the corresponding to the year 2015 since this one is the year before the declaration of insolvency proceedings in the case of the insolvent companies.

However, the information of years 2011, 2012, 2013, and 2014 has also been included, with the aim of analysing the accuracy of the models in the years prior to bankruptcy.

It should be noted that, on several occasions, the financial information of some insolvent companies was not available in the SABI platform. This can be explained by the fact that these companies have not deposited their annual accounts in the official registry. To solve this issue, the following company has been chosen from the list.

The companies that compose the sample of the solvent and insolvent companies are shown in **Electronic Appendix 1.A** and **Electronic Appendix 1.B**, respectively.
It is necessary to note that, in terms of the legal form of the companies of the sample, could appear the following terms: *Sociedad Limitada* (S.L.), private limited company; *Sociedad Anónima* (S.A.), public limited company; *Sociedad Limitada Unipersonal* (S.L.U.), sole proprietorship private limited company, and *Sociedad Anónima Unipersonal* (S.A.U.), sole proprietorship public limited company.

The financial information of the sample companies for the years 2015, 2014, 2013, 2012 and 2011; which is one, two, three, four and five years before bankruptcy, is shown in **Electronic Appendix 2.A** (solvent companies) and **Electronic Appendix 2.B** (insolvent companies) (Sistema de Análisis de Balances Ibéricos (SABI), 2017).

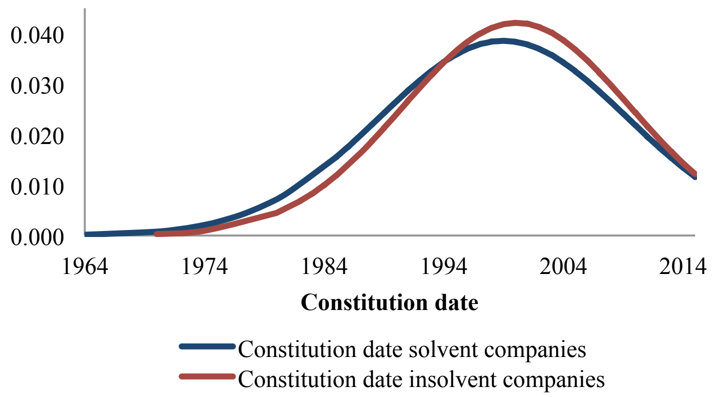
4.1.4. Sample description

In this section, the two sample groups (solvent and insolvent companies) will be compared to analyse the differences between both. The studied parameters will also be compared with those of all Spanish companies and the construction sector.

Regarding the first studied parameter, the date of constitution, as shown in Figure 17 the distribution of both groups is similar, showing a left-skewed distribution. This means, most of the data is located on the left side of the mean; thus, the majority of

the companies of the sample have been founded after 1999, in the case of the solvent firms, and after 2000, in the case of the insolvent ones.
Because the distribution is left-skewed, the median[3] is a better tool than the average to compare both groups. Therefore, while the median of the constitution date of the solvent companies is 2001, the median of the insolvent ones is 2002. Consequently, it can be stated that the insolvent companies of the sample are slightly younger than the solvent ones.

Figure 17. Distribution of the constitution date of the sample



Source: Own elaboration based on data from (Sistema de Análisis de Balances Ibéricos (SABI), 2017)

As presented in Table 1, most of the Spanish companies (65%) and those of the construction sector (72%), were founded after 2004. Therefore, the companies in the sample are older than the ones of the total Spanish companies and the total of the construction sector.

[3] The median is the value which divides the total frequency into two equal halves (Kendall, 1943).

Table 1. Constitution date of Spanish companies and those of the construction sector

	Total Spain		Construction sector	
1995 or before	476,953	14.97%	12,258	8.14%
1996 - 1999	278,852	8.75%	9,593	6.37%
2000 -2003	356,760	11.19%	19,361	12.86%
2004 - 2007	483,976	15.19%	40,729	27.04%
2011 - 2008	558,874	17.54%	30,362	20.16%
2012 - 2013	404,097	12.68%	11,063	7.35%
2014 - 2015	627,366	19.69%	27,233	18.08%
Total	3,186,878	100%	150,597	100%

Source: Own elaboration based on data from (Instituto Nacional de Estadísitca (INE), 2017)

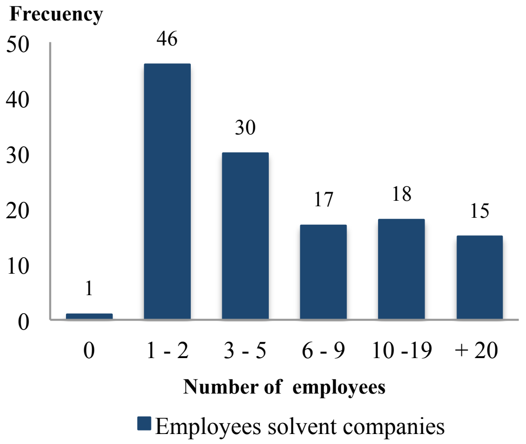
The number of employees of the companies in the sample**,** it has been represented as a histogram[4] (Figure 18 and Figure 19). However, 21 and 23 of the solvent and insolvent companies, respectively, do not provide this information, so they have not been included in the analysis.

The histogram of both solvent and insolvent companies is right-skewed, this means that most of the companies of the sample have few employees. In particular, one of the solvent companies and 43 (about 34%) of the insolvent companies have no employees. This may be because companies might have started firing employees, as it is one of the most recurring ways to reduce costs, or because they resort to Temporary Employ Agencies (TEA).

In the case of solvent companies, 46 of them (around 36%) have between one and two employees, and only 15 of them (about 12%) have more than twenty. Likewise, only 14 of the insolvent companies (almost the 12%) have more than twenty employees.

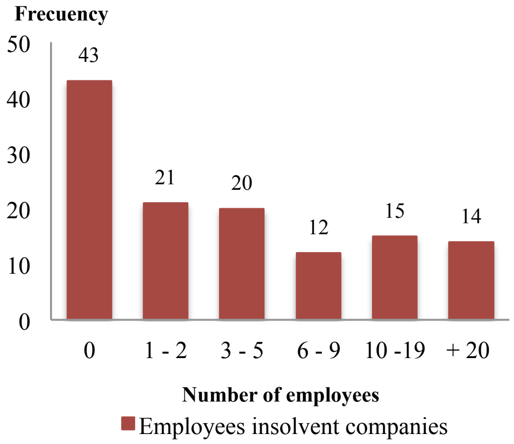
[4] A histogram is a graphical representation of a frequency. The horizontal axis is divided into intervals, the heights of which measure the frequency (Berenson, Levine, Szabat, & Krehbiel, 2012).

Figure 18. Histogram of the number of employees in the sample of solvent companies (2015)



Source: Own elaboration based on data of (Sistema de Análisis de Balances Ibéricos (SABI), 2017)

Figure 19. Histogram of the number of employees in the sample of insolvent companies (2015)

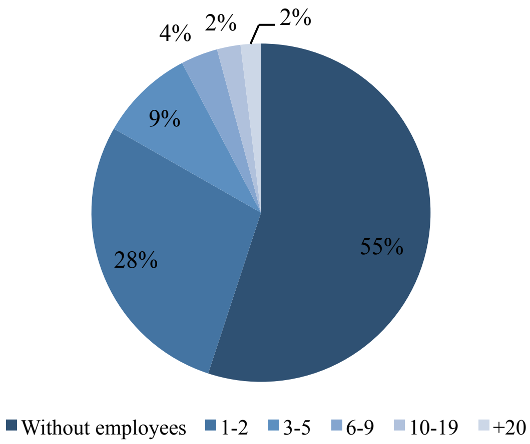


Source: Own elaboration based on data from (Sistema de Análisis de Balances Ibéricos (SABI), 2017)

From the point of view of size, measured in number of employees, Spanish companies are characterized by their small size. In particular, Figure 20 and Figure 21 show graphically the distribution of firms according to the number of employees.

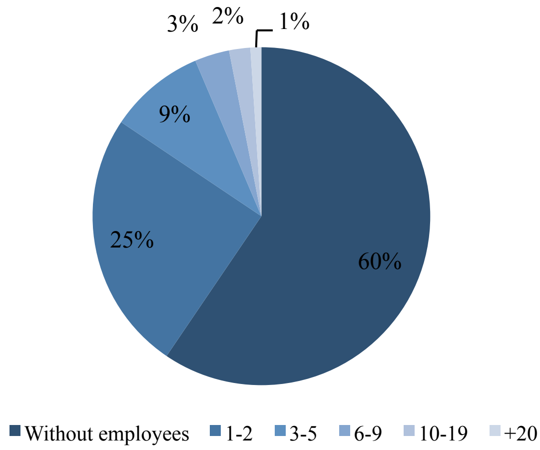
Most of the Spanish companies (55.04%) do not have any employee, this can be explained because they option to Temporary Employ Agencies (TEA), as discussed above. In the construction sector, in particular, 59.49% of the companies have no employees. Moreover, while 83.27% of the total of the Spanish companies and 84.40% of the construction companies have two or fewer employees, only 1.93% and 1.05%, respectively, have more than 20 employees.

Figure 20. Number of employees of the Spanish companies (2015)



Source: Own elaboration based on data from (Instituto Nacional de Estadísitca (INE), 2017)

Figure 21. Number of employees of the construction sector in Spain (2015)



Source: Own elaboration based on data from (Instituto Nacional de Estadísitca (INE), 2017)

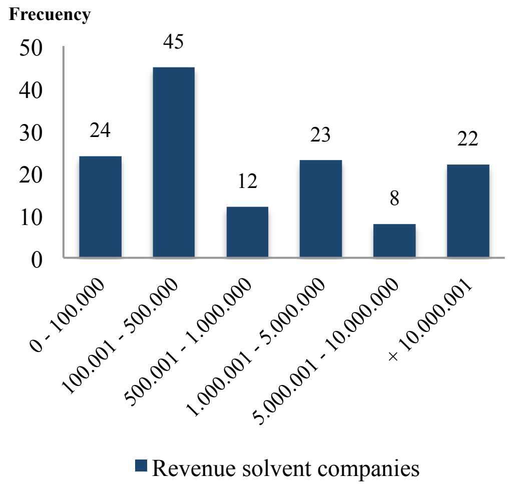
Regarding the revenue (Figure 22 and Figure 23), while the histogram of insolvent companies is right-skewed (most of the companies have a low revenue), the histogram of the solvent companies do not follow a normal distribution.

Most of the solvent companies (in particular, 45 of them), have a revenue between 100,001 and 500,000 euros. For their part, most of the insolvent companies (71 firms) have less than 100,000 euros of revenue; this is logical, considering that 2015 was the year before the declaration of insolvency proceedings.

However, it is important to note that 14 of the solvent companies and 30 of the insolvent ones do not provide information on their revenue, therefore were not included in the analysis.

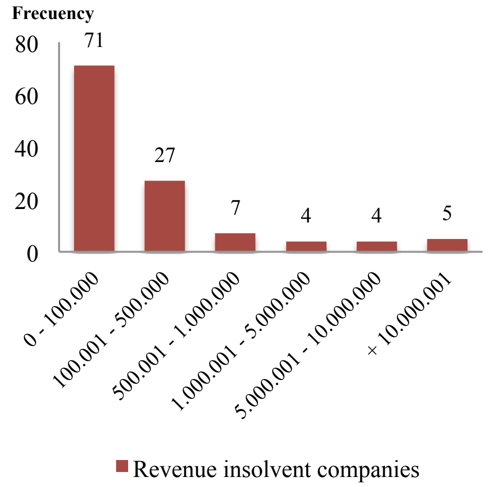
In this case, it is not possible to carry out the comparison with the total of Spain. Official webpages do not provide the revenue data divided into tranches and the total amount is extremely high, due to the large companies operating in the Spanish market. Therefore the analysis would be meaningless.

Figure 22. Histogram of the revenue of solvent companies (2015)



Source: Own elaboration based on data from (Sistema de Análisis de Balances Ibéricos (SABI), 2017)

Figure 23. Histogram of the revenue of insolvent companies (2015)



Source: Own elaboration based on data from (Sistema de Análisis de Balances Ibéricos (SABI), 2017)

4.2. Application of the models

Regarding the models that will be applied to the sample, Altman Z-Score will be chosen within the multivariate discriminant analysis,. Altman's model, apart from being one of the most popular has high accuracy, and offers several variations depending on the type of companies being studied.

Within the Logit and Probit analyses, the model that will be used is the one developed by Dr. James Ohlson. Ohlson's model, which follows the Logit approach, has high accuracy and is applicable for companies in general (Bellovary & Giacomino, 2007).

Various researchers suggest that industry attributes should be an important component in bankruptcy prediction, because different industries face different levels of competition, concentration, or accounting agreements, among others. In fact, even presenting identical financial statements, the probability of bankruptcy may differ between companies in different sectors (Chava & Jarrow, 2004). Thus, these arguments suggest setting specific sectoral models for each industry. Therefore, the model developed by Ihab Adel Ismail (Logit analysis focused on the construction sector) will be also applied to the sample.

4.2.1. Altman's model: Multivariate Discriminant Analysis

The model developed by Altman that is applicable to companies included in the construction sector is the Z''-Score, indicated for non-manufacturers. The Z''- Score model is written as follows (Altman, 2000):

$$Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$$

Where:

$$X_1 = \frac{\text{Working Capital}}{\text{Total Assets}}$$

$$X_2 = \frac{\text{Retained Earnings}}{\text{Total Assets}}$$

$$X_3 = \frac{\text{EBIT}}{\text{Total Assets}}$$

$$X_4 = \frac{\text{Book Value of Equity}}{\text{Total Liabilities}}$$

- Working capital to total assets (X_1) is a liquidity ratio that measures the net liquid assets of the company relative to the total capitalization. Working capital can be defined as the difference between current assets and current liabilities, and it expresses if the firm is able to pay its short-term debts with its current assets (Altman, 2000).

- Retained earnings to total assets (X_2) measures the profitability as a proportion of total assets. Retained earnings is the account which reports the total amount of reinvested earnings and/or losses of a firm over the time, this is, the percentage of net earnings not paid out as dividends, but retained by the company (Altman, 2000) (Investopedia).

- The ratio earnings before interest and taxes (EBIT) to total assets (X_3) is a profitability ratio that indicates the productivity of the company's assets. Altman holds the idea that this ratio is particularly appropriate for the corporate failure study since a firm's ultimate existence is based on the earning power of its assets (Altman, 2000).

- The ratio book value of equity to total liabilities (X_4) is a leverage ratio that expresses the proportion of own financing on the external financing. This is, how much the company's assets can reduce their value (measured by equity plus debt) before the liabilities exceed the assets and, consequently, the company becomes insolvent (Altman, 2000).

The zones of discrimination of the Z''-Score are the following:

- Z'' > 2.6 → Safe Zone
- 1.1 < Z''> 2.6 → Grey Zone
- Z'' < 1.1 → Distress Zone

The results of the model ratios and the value of the Z-Score for one, two, three, four and five years before bankruptcy for each company, are shown in **Electronic Appendix 3**.

4.2.2. Ohlson's model: Logit Analysis

The O-Score model, developed by Dr. James Ohlson in 1980, is written as follows (Ohlson, 1980):

$$\mathrm{O-Score} = -1.32 - 0.407\mathrm{X}_1 + 6.03\mathrm{X}_2 - 1.43\mathrm{X}_3 + 0.0757\mathrm{X}_4 - 2.37\mathrm{X}_5 - 1.83\mathrm{X}_6 + 0.285\mathrm{X}_7 - 1.72\mathrm{X}_8 - 0.521\mathrm{X}_9$$

Where:

$X_1 = \log\left(\frac{\text{Total Assets}_t}{\text{GNP}}\right)$

$X_2 = \frac{\text{Total Liabilities}_t}{\text{Total Assets}_t}$

$X_3 = \frac{\text{Working Capital}_t}{\text{Total Assets}_t}$

$X_4 = \frac{\text{Current Liabilities}_t}{\text{Current Assets}_t}$

$X_5 = \frac{\text{Net Income}_t}{\text{Total Assets}_t}$

$X_6 = \frac{\text{Funds From Operations}_t}{\text{Total Liabilities}_t}$

X_7 = 1 if a net loss for the last two years, otherwise, $X_7 = 0$

X_8 = 1 if Total Liabilities > Total Assets, otherwise, $X_8 = 0$

$X_9 = \frac{NI_t - NI_{t-1}}{|NI_t| + |NI_{t-1}|}$[5]

- Total assets to GNP (Gross National Product) price index level, quantifies the relative exposure of companies' assets as a percentage of the host country total GNP. In other words, it is a way of measuring the size of the companies in the sample (Investopedia).

  It should be noted that, following Ohlson's instructions, the GNP value to be taken is the one corresponding to the previous year of the balance sheet date. Therefore, the value corresponding to the year 2014 must be taken.
  Since the GNP index assumes a base value of 100 for 2003, the GNP variable of the model is calculated as follows:

$$\text{GNP} = \frac{\text{GNP}_{2014} \times 100}{\text{GNP}_{2003}} = \frac{1{,}037{,}025 \times 100}{803{,}472} = 129.07$$

- Total liabilities to total assets is a leverage ratio that defines the total amount of debt relative to assets. The greater the ratio, the greater the degree of leverage, and consequently, financial risk (Investopedia).

- Working capital to total assets has been explained in the previous section (Section 4.2.1.).

[5] NI: net income

- Current liabilities to current assets is a liquidity ratio that measures company's ability to pay short-term obligations. It indicates the percentage of current liabilities that can be satisfied with the most liquid resources (Investopedia).

- The ratio net income to total assets is called Return On Assets (ROA) or "return on investment" and is an indicator of how profitable a company is relative to its assets (Investopedia).

- Funds From Operations (FFO) to total liabilities is a measure of leverage. A high ratio implies the company is able to pay its debts from its operating income. Nevertheless, a low ratio means the company is highly leveraged. FFO can be defined as net income plus depreciation and amortization, less the gains on sales of property (Investopedia).

- The ratio $(NI_t - NI_{t-1})/(|NI_t| + |NI_{t-1}|)$ measures the change in net income with respect to the previous year.

If O-Score is greater than 0.038 the company can be classified in the distress zone, otherwise, the company is in the safe zone. Likewise, the same conclusion can be drawn with the ratio $\frac{\mathrm{Exp(O-score)}}{1+\mathrm{Exp(O-score)}}$; if it is greater than 0.5 the company is the distress zone, otherwise, the firm is in the safe zone.

The results of the model ratios and the value of the O-Score for one, two, three, four and five years before bankruptcy for each company, are shown in **Electronic Appendix 4**.

4.2.3. Ismail's model: Logit Analysis

Ismail developed eight different models with different ratios and coefficients (
Table 2), as well as different levels of accuracy (Table 3):

Table 2. Ratios and coefficients of Ismail's models

Model	Constant	ROA	ROC	EBITDA Margin	Gross Margin	Average Days Sales Out.	Average Days Payable Out.	Total liabilities to Total Assets
Model 1	-4.624	-7.327				0.022		3.630
Model 2	-3.407	-5.570					0.020	4.437
Model 3	-4.347		-4.474			0.021		3.385
Model 4	-3.411		-3.813				0.020	4.368
Model 5	-5.205			-2.548		0.024		4.356
Model 6	-4.240			-0.124			0.029	4.474
Model 7	-4.388				-3.526	0.026		4.242
Model 8	-4.085				-0.197		0.026	4.544

Source: Own elaboration based on (Ismail, 2014)

Table 3. Prediction accuracy of Ismail's models

Model	**Prediction Accuracy**		
	2 years before the failure	1 year before the failure	6 months before the failure
Model 1	68.09%	95.83%	100%
Model 2	85.11%	100%	100%
Model 3	72.34%	95.83%	100%
Model 4	85.11%	100%	100%
Model 5	70.21%	91.67%	100%
Model 6	80.85%	95.83%	100%
Model 7	91.49%	100%	100%
Model 8	80.85%	95.83%	100%

Source: Own elaboration based on (Ismail, 2014)

It is important to note that all the models proposed by Ismail include the ratio total liabilities to total assets. This is because Ismail considers that ratio is the most convenient to measure the liquidity of companies and, therefore, the most useful to predict the insolvency of Spanish construction companies.

Given the predictive capacity of the different models shown above, the model chosen to be applied is model 3, since, as Ismail announces, model 3 seems to offer the most balanced results for all prediction horizons. This model includes the ratios: return on equity (ROC), average days of outstanding sales and total liabilities to total assets.

This particular model was able to predict failure with an accuracy of 72.34% two years in advance, 95.83% onw year in advance, and 100% six months in advance; while maintaining an overall model accuracy rate of around 85%. Ismail's model 3 is written as follows:

$$E\ (y) = -4.34753 - 4.47484X_1 + 0.02188X_2 + 3.38579X_3$$

Where:

$X_1 = \frac{\text{EBIT}}{\text{Capital Employed}}$

X_2 = Average days sales outstanding = $\frac{\text{Accounts Receivable}}{\text{Total Credit Sales}} \times 365$

$X_3 = \frac{\text{Total Liabilities}}{\text{Total Assets}}$

- The ratio Earnings Before Interest and Tax (EBIT) to capital employed is also called Return on Capital (ROC). This ratio measures a company's profitability and the efficiency with which its capital is employed.
  Capital Employed is the value of all the assets employed in a business. It can be calculated by subtracting the current liabilities from total assets or adding the fixed assets to the working capital (Ismail, 2014).

- The ratio average days sales outstanding is a management ratio that indicates the time a company takes to collect revenue after a sale has been made (Ismail, 2014), therefore, it is an indirect way of measuring liquidity.

- Total liabilities to total assets has been explained in the previous section (Section 4.2.2.).

If E (y) ≥ 0 the company has a high probability of bankruptcy, otherwise, if E (y) < 0 the company is located in the safe zone.

The results of the model ratios and the value of the E (y) for one, two, three, four and five years before bankruptcy for each company, are shown in **Electronic Appendix 5**.

4.3. Analysis of the effectiveness of the models

In this section, the predictive capacity of the three models described above will be analysed, in order to determine which of these models is more appropriate to predict business insolvency in companies of the construction sector in Spain. It should be noted that the accuracy will be analyzed one year before the bankruptcy, as well as the years prior to bankruptcy.
Besides, with the aim of understanding which variables are more determinant to predict the insolvency of the companies in the sample, the ratios used by the models will be analysed.

4.3.1. Comparison of the accuracy of the models one year before the bankruptcy

Table 4, Table 5 and Table 6 show the results and accuracy given by Altman, Ohlson, and Ismail models, respectively, one year before the bankruptcy, that is 2015.

Table 4. Results of Altman's model one year before the failure

Observed	Forecasted			Correct percentage
	Safe	Distress	Grey	
Safe	98	21	29	66.22%
Distress	39	91	18	61.49%
Accuracy of the model				**63.85%**

Source: Own elaboration based on the results obtained when applying the model Z''- Score from (Altman, 2000)

Table 5. Results of Ohlson's model one year before the failure

Observed	Forecasted		Correct percentage
	Safe	Distress	
Safe	67	81	45.27%
Distress	12	136	91.89%
Accuracy of the model			**68.58%**

Source: Own elaboration based on the results obtained when applying the O-Score from (Ohlson, 1980)

Table 6. Results of Ismail's model one year before the failure

Observed	Forecasted		Correct percentage
	Safe	Distress	
Safe	105	43	70.95%
Distress	37	111	75.00%
Accuracy of the model			**72.97%**

Source: Own elaboration based on the results obtained when applying the Model 3 from (Ismail, 2014)

The accuracy of the model is the percentage of times the model has correctly predicted the solvency or insolvency of the companies within the construction sector in Spain. While the models of Altman and Ohlson present an accuracy of 63.85% and 68.58%, respectively, the accuracy of the third model of Ismail stands at 72.97%. It should be noted that the Altman model has been located in the grey zone 15.88% of the times; 29 times in the solvent companies and 18 times in the insolvent ones.

It is necessary to mention that the accuracy of the models when applied to the sample, differs significantly from the values affirmed by the studies. 64% in contrast to 96% in Altman's model, 69% in contrast to 96% in Ohlson's model, and 73% in contrast to 96% in Ismail's one.

4.3.2. Comparison of the accuracy of the models the years prior to bankruptcy

In this section, the accuracy obtained when applying the models to the sample two, three, four and five years before bankruptcy will be analysed. Although the results are included in **Appendix 4**, Table 7 shows a summary of the accuracy of each model for each year.

Table 7. Accuracy of the models the years prior to the bankruptcy

	Altman	Ohlson	Ismail
1 year before	63.85%	68.58%	72.97%
2 years before	52.30%	64.34%	57.04%
3 years before	48.88%	61.34%	56.27%
4 years before	46.61%	62.70%	53.91%
5 years before	49.79%	61.00%	55.90%

Source: Own elaboration based on the results obtained when applying the models of (Altman, 2000), (Ohlson, 1980) and (Ismail, 2014)

Despite, as mentioned above, Ismail's model is the one that presents the highest accuracy one year before bankruptcy, this situation changes when considering more years before the insolvency proceedings declaration.

In view of this information, it can be deemed that the model that has less predictive capacity is Altman's one. This model goes from an accuracy of 64% a year before bankruptcy to a 50% accuracy five years before bankruptcy. In other words, the predictive ability of the model is drastically reduced over the years, in particular by 22%.

On the contrary, Ohlson's model shows reasonably consistent results. Its predictive capacity is 68.58% a year before bankruptcy and it declines only up to 61% five years before bankruptcy, representing a decrease of 11%.

In the case of the Ismail model, it went from having the highest precision (72.97%) one year before bankruptcy to a 57% accuracy two years before bankruptcy, representing a decrease of almost 24%. After that moment, the predictive capacity of Ismail's model remained around 56% the rest of the years.

4.3.3. Model ratios analysis

At this point, the ratios used in each model will be analysed in order to determine how the models have been able to predict the insolvency of the companies.

4.3.3.1. Altman's model ratios analysis

Table 8 shows the average result of the ratios included in Altman's model and Table 9 displays the classification of these ratios.

Table 8. Average result of Altman's model ratios

		Coefficients	Solvents			Insolvents		
			Safe	Grey	Distress	Safe	Grey	Distress
X_1	$\frac{\text{Working Capital}}{\text{Total Assets}}$	6.56	0.52	0.10	-0.03	0.66	0.22	-1.28
X_2	$\frac{\text{Retained Earnings}}{\text{Total Assets}}$	3.26	0.08	0.04	-0.04	0.04	-0.02	-3.18
X_3	$\frac{\text{EBIT}}{\text{Total Assets}}$	6.72	0.09	0.06	-0.02	0.08	0.01	-1.22
X_4	$\frac{\text{Equity}}{\text{Total Liabilities}}$	1.05	45.98	0.44	0.30	0.42	0.34	-0.15
Z-Score			**52.55**	**1.70**	**-0,14**	**5.45**	**1.83**	**-27.09**

Source: Own elaboration based on the results obtained when applying the model Z''- Score from (Altman, 2000)

Table 9. Classification of Altman's model ratios

Altman model ratios		
X_1	Working capital to total assets	Liquidity ratio
X_2	Retained earnings to total assets	Profitability ratio
X_3	Earnings before interest and taxes to total assets	Profitability ratio
X_4	Book value of equity to total liabilities	Leverage ratio

Source: Own elaboration from (Altman, 2000)

As can be seen in the table above, the model is formed by two profitability ratios, a liquidity ratio, and a leverage ratio.

Unlike the other two models, all coefficients of the Altman's one are positive, meaning the higher the value of the ratio, the better. This makes sense given the nature of the liquidity and profitability ratios and, in the case of the leverage ratio, equity to total liabilities ratio indicates the proportion of own financing on the external financing. Therefore, the higher the ratio, the less indebtedness and, therefore, the less risk.

Although the four variables of the model present a similar pattern (the value of the ratios of the companies in the safe zone are higher than those in the distress zone), could be said that the most determining component for the classification is X_1, the ratio working capital to total assets (liquidity measure).

4.3.3.2. Ohlson's model ratios analysis

Table 10 shows the average result of the ratios included in Ohlson's model. However, the variables X_7 and X_8 have been analysed separately because they are binary.

Table 10. Average result of Ohlson's model ratios

		Coefficients	Solvents		Insolvents	
			Safe	Distress	Safe	Distress
X1	$\log\left(\frac{\text{Total Assets}_t}{\text{GNP}}\right)$	-0.407	4.10	3.68	4.30	3.74
X2	$\frac{Total\ Liabilities}{Total\ Assets}$	6.03	0.34	0.77	0.45	1.84
X3	$\frac{Working\ Capital}{Total\ Assets}$	-1.43	0.52	0.23	0.43	-0.67
X4	$\frac{Current\ Liabilities}{Current\ Assets}$	0.0757	0.34	0.79	0.66	5185.21
X5	$\frac{Net\ Income}{Total\ Assets}$	-2.37	0.06	0.02	0.14	-1.28
X6	$\frac{Funds\ From\ Operations}{Total\ Liabilities}$	-1.83	2.22	-0.04	0.35	-0.31
X9	$\frac{NI_t - NI_{t-1}}{\lvert NI_t\rvert + \lvert NI_{t-1}\rvert}$	-0.521	0.25	0.05	0.31	-0.10
O-Score			**-2.18**	**1.70**	**-5.85**	**1.65**

Source: Own elaboration based on the results obtained when applying the model O- Score from (Ohlson, 1980)

Table 11 shows the classification of the ratios included in Ohlson's model:

Table 11. Classification of Ohlson's model ratios

Ohlson's model ratios		
X_1	Total assets to GNP	Size ratio
X_2	Total liabilities to total assets	Leverage ratio
X_3	Working capital to total assets	Liquidity ratio
X_4	Current liabilities to current assets	Liquidity ratio
X_5	Net income to total assets (ROA)	Profitability ratio
X_6	Funds from operations to total liabilities	Leverage ratio
X_9	$(NI_t - NI_{t-1})/(\lvert NI_t\rvert + \lvert NI_{t-1}\rvert)$	Profitability ratio

Source: Own elaboration from (Ohlson, 1980)

Ohlson's model is formed by a size ratio, two leverage ratios, two liquidity ratios and two profitability ratios.

First and foremost, it is necessary to emphasize that unlike in Altman's model, in Ohlson's model the coefficients of some ratios are negative. Therefore, since companies with an O-Score lower than 0.5 are classified in the safe zone, the higher the result of a ratio with a negative coefficient, the better. Likewise, the lower the result of a ratio with a positive coefficient, the better.

Regarding the leverage ratios, the ratio total liabilities to total assets (X_2) indicates the degree of leverage, this is, the financial risk. Accordingly, since the lower, the better, the coefficient of this ratio is positive. On the other hand, FFO to total liabilities (X_6) has a negative coefficient because of the higher ratio the lower leverage and, consequently, risk.

In terms of liquidity ratios, working capital to total assets (X_3) is also included by Altman in his model. This ratio has a negative coefficient, so the higher, the better.

The other liquidity ratio, current liabilities to current assets (X_4), is the current ratio (current assets to current liabilities) upturned. It has a positive coefficient because if the quotient is high it means that the company is too indebted for its asset level.

Regarding the profitability ratios, while the ratio net income to total assets (X_5) indicates how profitable is a company in relation to its assets, the ratio (NI_t – NI_{t-1})/($|NI_t|$ + $|NI_{t-1}|$) (X_9) measures the change in net income with respect to the previous year. In this case, both profitability ratios have a negative coefficient.
It is worth mentioning that while Ohlson's model includes the ratio net income to total assets to measure profitability, Altman's model includes a similar one: earnings before interest and taxes (EBIT) to total assets, this is, Altman includes the income before contractual obligations must be paid.

Finally, with respect to the binary variables, X_7 adopts the value 1 if there was a net loss in the last two years and, otherwise, takes a null value. Consequently, since the coefficient of this variable is positive, this means the lower (0 in this case), the better. In terms of the results of this variable in the model, there was a net loss in 2013 or/and 2014 in the 44.59% of the solvent companies and in the 70.27% of the insolvent ones.

X_8 takes the value 1 if total liabilities exceed total assets and, otherwise, it adopts the value 1. This sign of this variable is not positive as expected because, as described by Ohlson in his research, the variable X_8 serves as a discontinuity correction for the variable total liabilities to total assets (X_2). Survival would depend upon many complex factors, therefore the effect of an extreme leverage position should be corrected. A positive sign would suggest almost certain bankruptcy, while a negative sign suggests that the situation is not that disastrous (Ohlson, 1980).
X_8 takes the value 0 in 99.32% of the cases of the solvent companies and in 56.08% of the cases of the insolvent ones. This means that most of the companies in both groups can pay their debts with their total assets.

In terms of the values taken by the ratios explained above, the pattern followed is similar, being high the ratios with a negative coefficient and low the ones with a positive coefficient in the companies classified as safe. However, it could be said that the variables that have been most significant for the classification between safe or distress, have been X_3, Working capital to total assets (liquidity ratio), and X_6, FFO to total liabilities (leverage ratio).

4.3.3.3. Ismail's model ratios analysis

The figures below show the average result of the ratios included in Ismail's model (Table 12) and the classification of these ratios (Table 13):

Table 12. Average result of Ismail's model ratios

		Coefficients	Solvents		Insolvents	
			Safe	Distress	Safe	Distress
X_1	$\frac{EBIT}{Total\ Assets - Total\ Liabilities}$	-4.47	0.18	-0.12	1.87	-16.41
X_2	$\frac{Accounts\ Receivable}{Total\ Credit\ Sales} \times 365$	0.02	48.88	1,417.95	52.22	861.47
X_3	$\frac{Total\ Liabilities}{Total\ Assets}$	3.39	0.57	0.60	0.87	1.92
E (y)			**-2.19**	**29.60**	**-8.62**	**94.43**

Source: Own elaboration based on the results obtained when applying the model 3 from (Ismail, 2014)

Table 13. Classification of Ismail's model ratios

Ismail's model ratios		
X_1	Return on Capital	Profitability ratio
X_2	Average Days Sales Outstanding	Management/liquidity ratio
X_3	Total Liabilities to Total Assets	Leverage ratio

Source: Own elaboration from (Ismail, 2014)

Since if E (y) ≥ 0 the company has a high probability of bankruptcy, as in Ohlson's model, the higher the result of a ratio with a negative coefficient, the better. Likewise, the lower the result of a ratio with a positive coefficient, the better.

With respect to the profitability, Ismail includes in his model the ratio Return on Capital (ROC) (X_1), which measures the efficiency with which its capital is employed. The coefficient of this ratio is negative; so the higher, the better since this implies that the company is carrying out a good management of the capital.

As a measure of management/liquidity, the model includes the average of days sales outstanding (X_2), avoiding to consider as collected the sales made ahead of time. In this case, logically the ratio has a positive coefficient; the fewer time companies take to collect sales, the better.

Respect the leverage, the ratio total liabilities to total assets (X_3) was also included in the Ohlosn's model. So, as stated above, the ratio measures the degree of leverage. Thus, the lower leverage, the better.

After analysing the ratios of Ismail's model it could be said that the variable that has been most significant for the classification between safe or distress in the sample analysed is X_2, average days sales outstanding (management/liquidity ratio).

5. Own model formulation

In this section a model able to predict business failure for Spanish construction companies will be created, using the sample of companies described above.

First of all, the variables making up the model will be selected, based on their appearance in previous models and their significance for the construction sector in particular. Secondly, the design of the initial model equation will be described, and a binary logistic regression will be used. Thirdly, the model will be created using a statistical program. In particular, two different statistical programs will be used, and therefore there will be two models. Finally, the two models will be compared to determine which one is most appropriate.

5.1. Selection of variables

Firstly, it is necessary to select the variables that will be part the model, and this means considering the previous literature in this scope and the analysis of the sector carried out in section 2.2. The variables under consideration are those that measure the following characteristics: liquidity, profitability, and leverage.

To measure liquidity, the most popular variables are: current ratio (used by 51 studies), working capital to total assets (present in 45 studies) and quick ratio

(included in 30 studies) (Bellovary & Giacomino, 2007). Moreover, as shown after the analysis of the construction sector (section 2.2.), the quick ratio is a representative variable to measure the liquidity of companies within this sector because it does not include inventories.
In addition to the ratios described above, this analysis will also include the ratio known as average days sales outstanding, which measures how long a company takes to collect the sales. This ratio, included by Ismail in his model, despite being a management ratio, faithfully shows the liquidity situation as displayed in section 2.2.6.

The most used profitability measure was Return On Assets (ROA), which was included in 54 studies, followed by retained earnings to total assets (used by 42 studies) and earnings before interest and taxes to total assets (incorporated in 35 studies) (Bellovary & Giacomino, 2007). Among these ratios, the ROA stands out as a measure of profitability of the companies within the construction sector in Spain.

The most popular leverage ratios are total liabilities to total assets (included in 46 studies) and equity to total debt (used by 16 studies) (Bellovary & Giacomino, 2007). Both are representative of the leverage situation of the sector, as it has been demonstrated in section 2.2.

Therefore, the variables to be considered in the model are the following (Table 14):

Table 14. Variables own model

Measured feature	Ratio
Liquidity	Current ratio
	Working capital to total assets
	Quick ratio
	Average days sales outstanding
Profitability	ROA
	Retained earnings to total assets
	EBIT to total assets
Leverage	Total liabilities to total assets
	Equity to total debt

Source: Own elaboration from (Bellovary & Giacomino, 2007)

5.2. Design of the model equation

Because the dependent variable will be binary (taking the value of 1 in case the company is solvent and 0 otherwise), linear regression is not applicable. This kind of regression is not appropriate when the dependent variable is categorical[6] since it does not respect the restriction that the values of the dependent variable oscillate between a series of values.

That is why it is more convenient to use a **logistic regression model** in this case. The generalized function for a logistic regression is the following:

$$P(Y) = \beta_0 + \beta_i X_i + \cdots + \beta_k X_k + \varepsilon$$

Where:

Y: dependent variable.

X_i: independent variables.

β_0: constant. It expresses the value of the probability of the dependent variable (Y) when the independent variables are zero.

β_i: logistic regression coefficients. They express the variation in the probability of Y, with a change of unit of the corresponding independent variable (X_i) when the remaining explanatory variables remain constant.

ε: estimation error.

In particular, in the model for predicting corporate insolvency of the construction sector in Spain, Y will be a binary variable that will take the value of 1 if the company is solvent and 0 otherwise, and X_i will be the result for each company of the ratios previously selected.

5.3. Implementation in the statistical program

To create the model, two different statistical software will be applied: Statistical Package for the Social Sciences (SPSS) and Minitab.

[6] In statistics, a categorical variable is a variable that can take a limited, and usually fixed, number of possible values, assigning the value on the basis of a qualitative characteristic (Starmes, Yates, & Moore, 2003).

5.3.1. Creation of the model with SPSS

SPSS is a statistical program developed by the corporation International Business Machines (IBM) in 1968. It is one of the best known and used statistical programs because of its ability to work with large databases and its simple interface. Its main functions are statistical analysis and reporting, predictive modeling and data mining, decision management and deployment, and big data analytics (IBM Webpage).

For the creation of the model with the software SPSS, a logistic regression has been carried out, choosing the following options: Regression → Binary logistic.

After the data of the companies of the sample was entered into the software, some of the variables were found to be not significant for the model. It should be mentioned that a variable is considered statistically significant when its p-value[7] is lower than the established level of significance (α), which in this case has been set as 0.05.

As a result of eliminating the non-significant variables, the variables of the model and their coefficients are shown below (Table 15). The report provided by the SPSS software is included in **Appendix 5**.

Table 15. Results displayed by SPSS

	β	Standard error	Wald	df [8]	Significance	Exp (β)
Total liabilities to total assets	-4.954	0.727	46.455	1	0.000	0.007
Average days sales outstanding	-0.001	0.000	12.974	1	0.000	0.999
Constant	4.373	0.605	52.324	1	0.000	79.267

Source: Own elaboration from the results displayed by SPSS

[7] The p-value of the test is the probability, assuming H_0 (null hypothesis) is true, that the test statistic would take a value as extreme or more extreme than that actually observed. The smaller the p-value, the stronger the evidence against H_0 provided by the data (Starmes, Yates, & Moore, 2003).

[8] df: degrees of freedom.

Therefore the resulting model is:

$$P(Y) = 4.373 - 4.954X_1 - 0.001X_2$$

Where:

X_1: total liabilities to total assets (leverage)
X_2: average days sales outstanding (management/liquidity)

If the value of P(Y) is greater than 0.5, the company is classified in the safe zone, otherwise, it is in the distress zone.

The coefficients of both variables are negative; this means that the lower value, the better, since the company will be classified as solvent if the value of P(Y) is greater than 0.5. This makes sense because of the variable X_1, total liabilities to total assets, measures the leverage, that is, the risk, and the variable X_2, average days sales outstanding, the days that the company takes to collect the revenue after the sale.

The coefficient of determination[9] of the SPSS proposed model is 41.7%, this means the model can explain more than 41% of the variation in results.

5.3.2. Creation of the model with Minitab

Minitab is a statistics program developed at the Pennsylvania State University in 1972. It has a multitude of tools to carry out the analysis of data and an orientation interface with an assistant that guides each step in the use of the program.

For the creation of the model with the software Minitab, the option "multiple linear regression analysis" has been executed. Solvency has been incorporated as a binary dependent variable and, with respect to the independent variables, an iterative process has been carried out because only five variables can be chosen at a time.

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[9] The coefficient of determination, or square of the correlation (R^2), is the fraction of the dependent variation in the values of the dependent variable (Y) that is explained by the model (Starnes, Moore, & Yates, 2003).

The first step of the iterative process was to include the following variables: total liabilities to total assets, quick ratio, net income to total assets, retained earnings to total assets, and equity to total debt. The report provided by Minitab in this first iteration is included in **Appendix 6.A**.

Since the equity to total liabilities variable was not significant for the model, it has been removed, and the ratio average days sales outstanding has been included. After this step, the most significant variables to predict the business insolvency were obtained: total liabilities to total assets (leverage) and average days sales outstanding (management/liquidity). The report provided by Minitab is included in **Appendix 6.B**. The resulting model is:

$$P(Y) = 0.9475 - 0.4021X_1 - 0.000724X_2 + 0.02729{X_1}^2$$

Where:

X_1: total liabilities to total assets
X_2: average days sales outstanding

As in the previous model, if the value of P(Y) is greater than 0.5, the company is classified in the safe zone, otherwise, it is in the distress zone.

The Minitab model has the same variables as the model created with SPSS. Thus, the coefficients of both variables are negative; this means that the lower the ratio, the better.

The coefficient of determination (R^2) of the proposed model above is 29.97%, meaning that the model can explain almost 30% of the variation in results.

5.4. Comparison of the models

The models created with both software have been applied to the sample of the construction sector. The results of the models and the values of P(Y) one, two, three, four and five years before bankruptcy are shown in **Electronic Appendix 6** (SPSS) and **Electronic Appendix 7** (Minitab). The accuracy of both models one year before bankruptcy is presented in the Table 16 and Table 17.

Table 16. Result of the model created with SPSS one year before bankruptcy

Observed	Forecasted		Correct percentage
	Safe	Distress	
Safe	95	53	64.19%
Distress	28	120	81.08%
Accuracy of the model			**72.64%**

Source: Own elaboration from the results displayed by SPSS

Table 17. Results of the model created with Minitab one year before bankruptcy

Observed	Forecasted		Correct percentage
	Safe	Distress	
Safe	128	20	86.49%
Distress	55	93	62.84%
Accuracy of the model			**74.66%**

Source: Own elaboration from the results displayed by Minitab

Both models have a relatively high accuracy one year before the bankruptcy; 72.64% in the case of the SPSS model and 74.66% in the case of the Minitab model. It should be noted that both models incorporate the same variables: total liabilities to total assets and average days sales outstanding.

While the model created with SPSS provides an R^2 of 41.7%, the one obtained with Minitab provides a value of 29.97%; this means that the SPSS model explains a greater proportion of variation in results. Therefore, a priori, it can be said that the SPSS model is better than the Minitab model.

At this point, it is necessary to evaluate the accuracy of the proposed models in the years prior to the bankruptcy. For this purpose, although the results are included in **Appendix 7**, Table 18 shows a summary of the accuracy of each model for each year.

Table 18. Accuracy of the proposed models the years prior to the bankruptcy

	SPSS	Minitab
1 year before	72.64%	74.66%
2 years before	68.31%	68.44%
3 years before	68.56%	61.36%
4 years before	65.43%	64.61%
5 years before	69.43%	60.70%

Source: Own elaboration based on the results obtained when applying the models created with SPSS and Minitab

The SPSS model goes from an accuracy of 72.64% a year before bankruptcy to 69.43% five years prior that time, which means a decrease in the predictive ability of 4.42%. The accuracy of the Minitab model is significantly reduced with time before bankruptcy increase, going from a predictive ability of 74.66% one year before to 60.70% five years before bankruptcy, which means a decrease of 18.70%

Nevertheless, to determine which model is more appropriate for the construction sector in Spain, both models will be applied to companies outside the sample. This is important because the statistical software is adapted to the specific sample to which it is applied, so sometimes it is complicated to extrapolate the model created.

For this purpose, a sample of 20 companies (ten solvents and ten insolvents), not included in the initial sample of 148 companies, has been randomly selected. The list of selected companies is included in **Electronic Appendix 8** and the financial information of these companies one, two, three, four and five years before bankruptcy is shown in **Electronic Appendix 9.A** (solvent companies) and **Electronic Appendix 9.B** (insolvent companies).
Besides, the results of the application of the models is shown in **Electronic Appendix 10** (SPSS) and **Electronic Appendix 11** (Minitab).

The accuracy of the models one year before the bankruptcy when extrapolated is shown in the following tables (Table 19 and Table 20).

Table 19. SPSS model results when extrapolated one year before bankruptcy

Observed	Forecasted		Correct percentage
	Safe	Distress	
Safe	7	3	70.00%
Distress	0	10	100.00%
Accuracy of the model			**85.00%**

Source: Own elaboration from the model created by SPSS

Table 20. Minitab model results when extrapolated one year before bankruptcy

Observed	Forecasted		Correct percentage
	Safe	Distress	
Safe	9	1	90.00%
Distress	3	7	70.00%
Accuracy of the model			**80.00%**

Source: Own elaboration from the model created by Minitab

Should be noted that when extrapolated, the accuracy one year before bankruptcy of the SPSS model (85%) is slightly higher than the Minitab one (80%).

Nevertheless, it is also important to evaluate the predictive capacity of the proposed models when extrapolated in the years prior to the bankruptcy. For this aim, although the results are included in **Appendix 8**, Table 21 shows the accuracy of each model for each year.

Table 21. Accuracy of the proposed models when extrapolated the years prior to the bankruptcy

	SPSS	Minitab
1 year before	85.00%	80.00%
2 years before	85.00%	68.42%
3 years before	84.21%	52.63%
4 years before	75.00%	68.75%
5 years before	66.67%	53.33%

Source: Own elaboration based on the results obtained when applying the models created with SPSS and Minitab

In the case of the companies outside the initial sample, while the SPSS model maintains a high accuracy over the years before bankruptcy, the predictive ability of the Minitab model is notably reduced with time before bankruptcy increases.

Therefore, given all the factors described above, it can be concluded that the model obtained through SPSS is more appropriate than that of Minitab, although both can be considered suitable.

6. Non-financial factors

Failure is the outcome of a complex process and it does not depend on a single factor. Therefore, apart from the reasons that cause the insolvency situation, which have been revealed throughout this study, there are non-financial factors that affect the risk of insolvency. These factors, which often lead to financial results, are essential to determine the future of a company; therefore, they are studied in this section.

According to the study of Robert D. Boyle & Harsha B. Desai (1991), the causes of failure can be expressed by an environment-response matrix distribution. The environment factor can be divided into two categories: internal environment, which represents the events that are under the management's control, and external environment, which corresponds to those that are beyond it. The response is also divided into two categories: administrative responses, which represent the short-term operational activities, and strategic ones, which represent the long-term planning of the company (Boyle & Desai, 1991).

As shown in Table 22, the environment-response matrix distribution can be adapted to the construction sector using the factors described by Dun and Bradstreet Corporation (1996):

Table 22. Environment-response matrix construction sector

	Administrative response	Strategic response
Internal environment	- Budgetary issues - Human and organizational issues	- Issues of adaptation to market conditions
External environment	- Business issues	- Macroeconomic issues

Source: Own elaboration from (Boyle & Desai, 1991) and (Dun and Bradstreet Corporation, 1996)

Therefore, this section will be divided into internal administrative factors, internal strategic factors, external administrative factors and external strategic factors.

It is important to note that when these factors are combined to create a poor company performance, the result is frequently the loss of financial capacity, which causes insolvency risk (Rice, 2013).

6.1. Internal administrative factors

There are two types of internal administrative factors: budgetary issues, and human and organizational issues.

Budgetary issues are based on financial data, which has been described in the previous sections. The following features of the construction sector stand out as typical: high leverage (companies within this sector tend to boost their projects through debt or their own results), low capital, insufficient profits, high average days sales outstanding, and high stock period.

Human and organizational issues include factors like poor working habits and the lack of business knowledge, managerial experience, and commitment, among others.

6.2. Internal strategic factors

Internal strategic factors consist of issues of adaptation to market conditions. In particular, these problems are related to inadequate sales, non-competitiveness, and overexpansion.

Regarding inadequate sales, most of the real estate entails great uncertainty about whether it will sell or rent its properties. General economic conditions, alternative investment methods, location, design, and quality are among the factors that affect the level of demand in this industry.

Concerning the non-competitiveness, the nature and intensity of competition in a market depend on several factors: the threat of new entrants, the threat of substitute products or services and the bargaining power of buyers and suppiers (Porter, 1980). Therefore, a company must be different enough to have a unique competitive advantage, especially in a supersaturated market such as construction. An understanding of these factors explained by Porter provides the basis for a strategic action agenda.

Overexpansion can lead a company to a high risk derived from investments with financial debt, which increases the chances of becoming insolvent. Expansion to new markets, such as projects in other states, and the search for different niches without proper preparation, can lead to high risks; therefore, this situation should be avoided. Overexpansion also means carrying out too many projects that the company can not afford; even if it can, overexpansion is risky due to external factors, as was the financial crisis. It must also be mentioned that the poor selection of projects can result in an unprofitable year or even determine the failure of the company.

6.3. External administrative factors

External administrative factors consist of the mind of the manager and business conflicts. For the former, according to Myers-Briggs Type Indicator (MBTI), there are sixteen personality types based on the perception and judgments of each individual of different scenarios or situations (Myers and Briggs Foundation).
In the study carried out by the Fails Management Institute (FMI), it is stated that certain mentalities increase the likelihood of a company having problems. In particular, in 62% of the company failure cases, an excessive ego was related to the actions leding up to the failure. In particular, the failure to lead a group is linked to some characteristics, such as pride, arrogance, and over-optimism (Rice, 2013).

The latter factor, that is business conflicts, can arise from the following situations (Handy, 1993): overlapping of formal objectives, ambiguity in role definition, multiplicity of assumed roles, confusion in contractual relationships, and hidden objectives.
It has been proven that the greatest number of conflicts occur in organizational systems and in quality and control issues, whereas in a single project they occur in the stage of design (Gardiner & Simmons, 1995).

6.4. External strategic factors

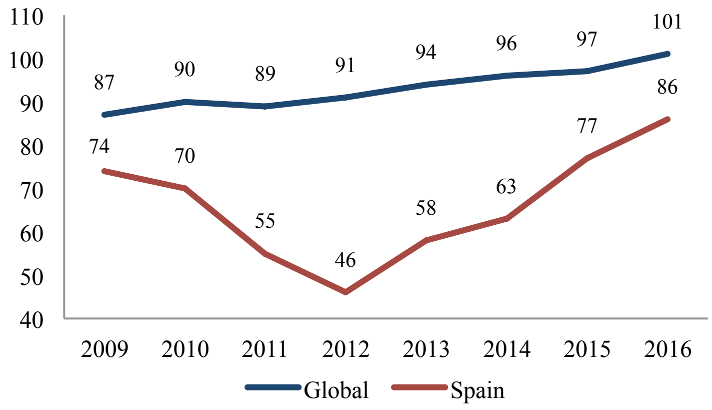
The external strategic factors can refer to natural factors or macroeconomic issues. The natural factors, apart from referring to disasters, are also related to the construction sector cycle. The construction sector has a cyclical nature, which implies that the activity rises and falls faster than the overall economy.

In the demand of the construction sector, the economic situation and the economic prospects of each person are primordial for making the purchasing decision. Therefore, the recovery of the demand for housing is one of the later consumption decisions, and consequently, the rent effect acts late compared to the rest of the goods.

Macroeconomic issues can be derived from different economic conditions, among which consumer confidence and interest rates stand out.

The consumer confidence is nearly always determined by national economic conditions, rather than by global events. However, the 2008 financial crisis originated in the United States (US) seriously affected the consumer confidence worldwide due to the importance of the US economy in the global one (Keely, 2016). Figure 24 shows the global and Spanish consumer confidence from 2009 to 2016 (Nielsen, 2016). It is important to note that while the global index followed an increasing trend in the period, growing from 87 to 101 points, the Spanish index fell from 74 to 46 points between 2009 and 2012, showing the devastating effect of the crisis in Spain. Nevertheless, it experienced an increase from 2013, reaching 86 points in 2016.

Figure 24. Consumer confidence (2009-2016)



Source: Own elaboration based on data from (Nielsen, 2016)

Interest rates are the amount that is paid for each unit of capital invested. The interest rate defines what an individual or company pays for a certain financing. This financing cost depends not only on the credit-worthiness of the company but also on other aspects related to the general functioning of the economy. A low-interest rate favors investment and gives companies greater liquidity to meet their current expenses or to increase the business and at the same time, also affects individuals. Therefore, it is a very important parameter to study, which affects in a very direct way the business development of every company (Jermann & Yue, 2013).

Apart from the above mentioned, other economic factores cause macroeconomic issues, including variables such as demographics, bonding issues, tax law, or government policy.

7. Conclusions and final discussion

The Spanish economy was one of the most affected by the economic crisis of 2008, in particular the construction sector that experienced devastating effects due to the housing bubble of the previous years. As a result, many companies were forced to close, causing an increase in the number of insolvency proceedings to unprecedented levels. Specifically, in the construction sector of Spain this number increased by approximately 199% in the period from 2008 to 2012.

After carrying out a financial analysis of the Spanish construction sector, can be concluded that it has low capital level, insufficient profits, high average collection period, high stock period and high level of leverage. Therefore, in order to apply the business prediction models to firms in the construction sector, these aspects must be taken into account.

There are multiple studies with the aim of predicting corporate insolvency, among which the Multiple Discriminant Analysis (MDA), and the Logit and Probit analyses stand out. Within the MDA analysis, Altman's study stands out, whereas the Logit and Probit analyses, Ohlson's study stands out. Also, within the Logit analysis, Ismail's model is worth being noted, a specific model for the construction sector.

These models have been applied to a sample of companies with the purpose of analysing their predictive capacity in the context of the construction sector in Spain. After applying them, it has been observed that, in terms of the predictive capacity of the models, Altman's model has been proven to be the one with the lowest accuracy. Altman's model goes from an accuracy of 64% a year before bankruptcy to 50% five years prior that time. As for Ismail and Ohlson's models, while Ismail model has the highest predictive capacity a year before bankruptcy (73%) in comparison to that of Ohlson (66%), Ohlson's model maintains a more stable accuracy in the years prior to bankruptcy.
The applicability of the models has proven to be low due to several factors. On the one hand, these models were developed in a very different economic situation, especially given the financial crisis that had a great impact on the Spanish economy. On the other hand, Altman and Ohlson's models are not specific to the construction sector, which has particular characteristics that differentiate it significantly from other sectors.

With the aim of obtaining a specific model for companies in the construction sector in Spain, two models have been proposed. These models have been obtained through the software SPSS and Minitab, following in both cases a binary logistic regression.

The two proposed models have a high accuracy one year before the bankruptcy; 72.64% and 74.66%, respectively. However, the SPSS model shows a greater accuracy the years prior to bankruptcy and its coefficient of determination is higher than the Minitab one (42% versus 30%). Moreover, when extrapolated, the accuracy obtained is significantly higher in the case of the SPSS model, both one year before bankruptcy and in previous years. Consequently, the model created with the software SPSS is better than the one created with Minitab.

Thus, it can be concluded that in the case of companies in the construction sector in Spain, both proposed models far exceed the predictive ability of Altman, Ohlson and Ismail models.

Business insolvency depends on the joint effect of many factors, where financial ones are usually a consequence of those that do not have a financial nature. As proven in this study, there are multiple non-financial factors, such as the over-expansion or the consumer confidence, that drastically influence the solvency of the companies. However, these factors are difficult to measure.

7.1. Limitations of the study

Among the limitations faced during the current study, are those related to the applicability of the corporate insolvency prediction models. The suitability of these models depends on the country in which the company is located, as well as the sector in which it operates. Therefore, it may not be suitable for other countries or sectors.

Moreover, another limitation is the difficulty of extrapolating the models since they adapt to the sample on which they are based for their formulation. Thus, it is possible that a model applicable to a sample of companies may not be suitable for another.

It should be also mentioned that the financial information of some of the insolvent companies of the initial sample was not available. The sample was randomly selected from the list of insolvency proceedings declared in 2016, and some of the companies had not deposited the accounts in the official registry. The financial information of these firms is accordingly not available in the database. This limitation has been solved by choosing the following company in the list of insolvent firms.

Furthermore, the annual accounts may be manipulated by the company and, therefore, not faithfully represent the situation of the firm. This limitation affects the study of financial information, the application of models to the sample of companies, and the creation of the proposed models.
The solution to it would be the audit of the firms’ financial statements. However, most companies, because of their size, do not exceed the limits to be necessarily audited.

The difficulty of obtaining non-financial information of the companies is also a limitation to consider. Although the financial information of Spain's construction companies has been successfully analysed, the non-financial information of these firms could not be obtained, since during the study period there was no organization that provided it. Therefore, this information, so decisive for the success of the companies, has not been included in the creation of the proposed models.

Finally, there are other methods to measure the insolvency of companies, as the new research alternatives through the application of artificial intelligence techniques. Nevertheless, these methods have not been taken into consideration in the current thesis because to carry out them it is necessary to have access to a much higher computing and processing capacity, which is unavailable for this study.

7.2. Future research

There are multiple possibilities that serve as a basis for future research from the current study; in particular, two future research lines are proposed.

Although the current study has focused on financial variables, a more in-depth one of non-financial variables and their inclusion in a model to predict corporate insolvency is proposed as future research. For this aim, it would be essential to have the necessary information on the non-financial factors of the companies and to find a way of measuring them.

The other suggested future research is to extrapolate the proposed models, obtained through the SPSS and Minitab software, to other countries or to other sectors and evaluate their applicability. Despite the differences between companies from different countries and sectors, it is possible to successfully apply the models.

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9. Appendices

Appendix 1.A. Financial information of the construction sector in Spain

BALANCE SHEET CONSTRUCTION SECTOR											
Monetary values in thousands of euros											
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
ASSETS											
A) Non-current assets	**20,731,483**	**22,291,829**	**26,701,613**	**20,753,452**	**34,530,831**	**35,761,999**	**36,377,284**	**35,041,249**	**32,873,346**	**31,818,709**	**16,479,0**
I. Intangible assets	1,377,115	1,462,843	1,657,229	169,754	282,899	276,434	265,954	270,267	295,173	322,633	169,9
II. Property, plant and equipment and real estate investments	14,572,189	15,519,236	18,939,031	16,207,479	26,139,183	26,737,071	26,918,940	25,763,957	23,936,740	23,032,328	12,021,7
III. Long-term financial investments	4,782,180	5,309,750	6,105,352	4,376,219	8,108,750	8,748,495	9,192,390	9,007,025	8,641,433	8,463,748	4,287,3
A) Current assets	**43,190,026**	**51,205,889**	**62,470,644**	**42,537,973**	**72,522,521**	**69,061,250**	**63,564,870**	**54,032,649**	**50,579,763**	**47,931,144**	**24,275,9**
I. Non-current assets held for sale	0	0	0	19,587	34,384	54,345	40,909	56,057	54,376	49,496	16,8
II. Inventories	22,478,203	27,213,525	36,206,460	23,501,909	45,583,362	42,402,468	39,286,679	32,467,701	31,019,273	28,496,459	14,226,9
III. Trade and other receivables	12,853,389	15,071,929	16,749,800	11,163,045	14,171,535	13,984,994	12,633,337	10,809,642	9,609,969	9,518,491	4,872,2
IV. Short-term financial investments	3,194,049	3,731,975	4,333,383	3,941,589	7,025,634	7,139,217	6,806,676	6,404,776	5,909,690	5,730,114	2,738,3
V. Cash and cash equivalents	4,615,339	5,132,366	5,108,265	3,872,687	5,638,923	5,416,735	4,723,632	4,229,240	3,922,912	4,079,491	2,393,4
VI. Accrual Adjustments	49,045	56,094	72,736	39,157	68,683	63,492	73,639	65,233	63,543	57,093	28,0
TOTAL ASSETS	**63,921,509**	**73,497,718**	**89,172,256**	**63,291,426**	**107,053,352**	**104,823,250**	**99,942,155**	**89,073,898**	**83,453,109**	**79,749,853**	**40,755,0**

Monetary values in thousands of euros

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
EQUITY AND LIABILITIES											
A) Equity	**20,764,858**	**23,143,265**	**27,390,384**	**20,312,758**	**34,847,056**	**37,009,505**	**37,360,680**	**36,233,337**	**35,420,752**	**35,588,252**	**18,670,35**
I. Capital and reserves without valuation adjustements	20,551,999	22,954,781	27,205,637	20,261,657	34,768,315	36,943,482	37,436,510	36,223,870	35,354,540	35,508,868	18,634,67
II. Valuation adjustements in equity	101,036	90,937	82,841	3,252	8,373	7,280	-140,290	-54,755	10,490	22,946	6,89
III. Grants, donations and bequests received	111,823	97,547	101,906	47,849	70,369	58,742	64,460	64,221	55,722	56,439	28,78
B) Non-current liabilities	**17,000,914**	**20,506,449**	**28,323,939**	**19,796,364**	**38,813,213**	**35,995,345**	**33,689,569**	**27,555,014**	**24,923,251**	**22,368,039**	**11,137,41**
I. Non-current payables with special features	0	0	0	19,939	15,126	21,775	148,607	22,304	15,281	15,201	3,72
II. Long-term external resources	16,834,205	20,342,882	28,095,791	19,499,707	38,303,019	35,517,862	33,111,920	27,107,873	24,527,192	21,939,934	10,980,31
III. Provisions	166,709	163,566	228,148	276,718	495,069	455,708	429,042	424,837	380,778	412,904	153,38
C) Current liabilities	**26,155,737**	**29,848,005**	**33,457,933**	**23,182,304**	**33,393,083**	**31,818,400**	**28,891,906**	**25,285,548**	**23,109,107**	**21,793,562**	**10,947,24**
I. Liabilities related to non-current assets held for sale	0	0	0	1,387	3,973	1,886	10,821	5,114	3,430	5,080	1,98
II. Short-term financing at cost	7,942,961	9,299,735	10,808,728	5,185,858	7,168,894	6,566,637	5,666,560	4,875,323	4,252,685	3,831,715	2,024,55
III. Short-term financing at no cost	18,212,776	20,548,270	22,649,205	17,995,060	26,220,216	25,249,877	23,214,526	20,405,111	18,852,991	17,956,767	8,920,70
TOTAL EQUITY AND LIABILITIES	**63,921,509**	**73,497,718**	**89,172,256**	**63,291,426**	**107,053,352**	**104,823,250**	**99,942,154**	**89,073,898**	**83,453,109**	**79,749,853**	**40,755,01**

PROFIT AND LOSS ACCOUNT CONSTRUCTION SECTOR											
Monetary values in thousands of euros											
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
I. Revenue	37,991,586	42,892,342	45,123,565	34,355,247	37,882,333	34,071,456	28,555,873	23,220,157	19,014,608	20,181,292	11,615,097
II. Consumptions	948,367	1,107,916	819,121	2,868,133	4,058,269	2,846,292	2,067,348	1,533,499	998,963	1,166,741	-534,287
GROSS MARGIN	**37,043,219**	**41,784,426**	**44,304,444**	**31,487,115**	**33,824,064**	**31,225,164**	**26,488,525**	**21,686,658**	**18,015,645**	**19,014,551**	**12,149,383**
I. Changes in finished goods and work in progress inventories	354,783	582,912	400,302	1,189,592	478,111	-843,073	-133,691	-482,740	114,876	-27,075	-78,418
II. Work carried out by the company for assets	40,485	21,333	16,514	104,515	239,397	169,927	152,187	158,799	80,637	74,270	57,559
III. Other operating income	902,314	965,427	1,196,306	547,159	871,097	892,214	897,945	813,366	722,254	719,314	382,317
IV. Net purchases and work done by other companies	-21,731,074	-24,702,283	-25,428,484	-19,447,462	-20,416,781	-17,237,499	-14,659,518	-11,562,613	-9,429,214	-10,055,469	-5,771,524
V. Changes in goods and prime materials	149,536	107,284	89,439	-879	-47,965	-69,326	14,899	-59,430	-58,594	-54,471	-5,732
VI. Personal expenses	-9,218,269	-10,315,667	-10,977,890	-9,694,623	-11,053,124	-10,320,170	-9,409,398	-7,789,632	-6,592,474	-6,611,633	-3,716,297
VII. Other operating expenses	-4,894,372	-5,406,537	-5,895,154	-4,800,891	-5,669,601	-5,321,548	-4,949,847	-4,271,658	-3,634,054	-3,573,166	-1,921,802
EBITDA	**2,646,622**	**3,036,896**	**3,705,476**	**-615,475**	**-1,774,803**	**-1,504,313**	**-1,598,899**	**-1,507,250**	**-780,924**	**-513,680**	**1,095,486**
VIII. Impairment and gains/losses on disposals of non-current assets	422,392	558,394	387,242	27,420	-30,687	-114,857	-273,821	-264,491	-180,524	-121,679	-44,454
IX. Amortization and depreciation charges on non- current assets and provisions surpluses	-979,027	-1,055,380	-1,298,435	-925,269	-1,220,672	-1,142,390	-1,076,853	-935,820	-763,754	-660,888	-340,865
PROFIT/LOSS FROM OPERATIONS (EBIT)	**3,038,354**	**3,647,827**	**3,613,404**	**1,354,810**	**1,032,107**	**84,733**	**-882,225**	**-1,174,062**	**-726,239**	**-129,505**	**175,881**
I. Financial income	350,165	468,340	589,361	326,188	440,027	342,221	364,801	324,712	285,090	222,587	102,844
II. Financial expenses	785,953	1,019,474	1,610,972	1,265,246	1,871,568	1,404,789	1,320,643	1,054,541	742,372	609,788	281,767
III. Change in fair value of financial instruments	35,485	51,358	24,447	1,823	125,213	114,474	105,181	-25,089	152,210	194,869	55,950
NET FINANCIAL INCOME/EXPENSE	**-400,303**	**-499,776**	**-997,164**	**-937,236**	**-1,306,328**	**-948,094**	**-850,661**	**-754,917**	**-305,072**	**-192,332**	**-122,973**
PROFIT/LOSS BEFORE TAX	**2,638,051**	**3,148,051**	**2,616,240**	**417,574**	**-274,221**	**-863,361**	**-1,732,885**	**-1,928,979**	**-1,031,311**	**-321,837**	**52,908**
Income tax	836,188	973,791	773,738	261,050	189,205	84,967	-57,104	-17,161	9,622	95,943	95,880
PROFIT/LOSS OF THE YEAR	**1,801,863**	**2,174,260**	**1,842,502**	**156,524**	**-463,426**	**-948,328**	**-1,675,781**	**-1,911,818**	**-1,040,933**	**-417,780**	**-42,972**

Appendix 1.B. Financial information of the industrial sector in Spain

BALANCE SHEET INDUSTRIAL SECTOR											
Monetary values in thousands of euros											
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
ASSETS											
A) Non-current assets	**105,592,809**	**113,738,761**	**129,554,949**	**137,639,321**	**146,210,560**	**158,445,139**	**162,136,432**	**164,436,361**	**137,678,488**	**138,010,110**	**103,036,657**
I. Intangible assets	6,526,143	7,334,471	7,260,630	6,334,247	6,896,054	7,518,518	7,612,896	9,587,644	8,779,505	9,614,020	7,565,325
II. Property, plant and equipment and real estate investments	56,295,237	59,079,056	62,641,724	60,390,991	70,674,278	71,269,907	73,126,687	76,608,784	73,604,492	73,536,692	55,991,674
III. Long-term financial investments	42,771,429	47,325,234	59,652,595	70,914,083	68,640,228	79,656,715	81,396,849	78,239,933	55,294,491	54,859,398	39,479,659
A) Current assets	**119,144,976**	**132,562,686**	**142,139,547**	**122,720,680**	**136,602,644**	**151,756,597**	**155,595,190**	**162,269,029**	**153,428,678**	**153,357,462**	**111,981,695**
I. Non-current assets held for sale	0	0	0	248,905	198,085	423,034	163,184	224,534	224,204	869,728	485,466
II. Inventories	31,274,766	34,820,446	37,775,506	33,341,667	35,094,627	39,976,486	41,679,314	43,604,652	40,859,944	39,834,923	26,832,017
III. Trade and other receivables	63,281,162	71,235,141	74,935,591	60,692,128	67,428,448	74,000,178	75,872,717	79,226,391	73,807,830	74,158,935	55,458,396
IV. Short-term financial investments	17,768,167	18,779,028	21,360,115	18,376,365	20,108,721	22,964,097	24,630,703	26,912,878	25,817,068	24,359,749	18,761,545
V. Cash and cash equivalents	6,466,931	7,284,536	7,676,562	9,761,615	13,355,227	13,955,850	12,827,688	11,864,591	12,317,570	13,706,579	10,142,783
VI. Accrual Adjustments	353,951	443,534	391,774	300,000	417,536	436,952	421,584	435,983	402,063	427,548	301,489
TOTAL ASSETS	**224,737,786**	**246,301,446**	**271,694,497**	**260,360,000**	**282,813,205**	**310,201,736**	**317,731,622**	**326,705,390**	**291,107,165**	**291,367,572**	**215,018,353**

Monetary values in thousands of euros

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
EQUITY AND LIABILITIES											
A) Equity	**83,671,123**	**90,352,566**	**96,805,467**	**99,389,484**	**106,905,747**	**124,001,112**	**129,190,158**	**133,740,777**	**118,488,343**	**120,638,184**	**89,907,542**
I. Capital and reserves without valuation adjustements	79,298,613	85,691,586	92,638,425	97,450,299	104,705,979	121,768,390	127,171,804	131,464,790	116,533,041	118,735,621	88,676,373
II. Valuation adjustements in equity	2,517,055	2,614,725	2,125,712	336,740	213,401	143,382	-36,491	82,687	39,489	16,204	-493
III. Grants, donations and bequests received	1,855,455	2,046,255	2,041,330	1,602,444	1,986,367	2,089,340	2,054,846	2,193,300	1,915,813	1,886,358	1,231,662
B) Non-current liabilities	**39,304,309**	**44,735,123**	**56,515,377**	**56,651,500**	**60,579,507**	**67,659,976**	**66,079,210**	**70,178,047**	**56,849,102**	**56,272,826**	**43,803,224**
I. Non-current payables with special features	0	0	0	151,504	1,340,101	1,194,939	2,005,998	1,873,639	2,146,451	2,017,608	981,522
II. Long-term external resources	33,738,090	38,667,529	50,913,269	50,854,438	53,767,156	61,109,649	59,347,307	63,293,892	49,305,561	49,480,334	38,716,621
III. Provisions	5,566,219	6,067,594	5,602,108	5,645,558	5,472,250	5,355,388	4,725,906	5,010,516	5,397,091	4,774,884	4,105,081
C) Current liabilities	**101,762,354**	**111,213,758**	**118,373,653**	**104,319,016**	**115,327,950**	**118,540,648**	**122,462,253**	**122,786,566**	**115,769,719**	**114,456,563**	**81,307,586**
I. Liabilities related to non-current assets held for sale	0	0	0	42,167	49,820	49,699	7,025	31,396	41,406	110,148	54,753
II. Short-term financing at cost	33,286,624	36,969,505	37,766,299	38,047,056	42,205,517	36,764,857	42,909,410	39,376,015	39,694,204	36,708,141	25,507,069
III. Short-term financing at no cost	68,475,730	74,244,253	80,607,354	66,229,793	73,072,613	81,726,092	79,545,819	83,379,155	76,034,110	77,638,274	55,745,764
TOTAL EQUITY AND LIABILITIES	**224,737,786**	**246,301,447**	**271,694,497**	**260,360,001**	**282,813,205**	**310,201,736**	**317,731,622**	**326,705,390**	**291,107,165**	**291,367,572**	**215,018,353**

PROFIT AND LOSS ACCOUNT INDUSTRIAL SECTOR

Monetary values in thousands of euros

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
I. Revenue	256,327,848	283,493,088	305,664,408	272,688,183	238,579,013	265,720,352	291,431,030	316,674,702	306,012,714	309,978,654	238,117
II. Consumptions	-11,775,182	-14,326,067	-17,410,250	-30,470,023	-24,898,066	-27,695,936	-30,749,517	-35,999,007	-32,517,732	-31,409,796	-25,626
GROSS MARGIN	**268,103,030**	**297,819,155**	**323,074,658**	**303,158,206**	**263,477,080**	**293,416,288**	**322,180,547**	**352,673,709**	**338,530,446**	**341,388,450**	**263,744**
I. Changes in finished goods and work in progress inventories	1,030,026	1,046,036	1,235,346	62,981	-1,829,516	1,263,062	1,914,078	-120,018	-537,438	-652,755	-81
II. Work carried out by the company for assets	865,791	832,516	864,319	996,090	1,030,860	1,027,165	1,110,247	1,270,293	1,165,342	1,202,201	908
III. Other operating income	3,381,602	3,534,670	3,995,080	4,003,788	4,044,311	4,483,171	5,085,595	5,133,924	4,741,297	4,583,387	3,793
IV. Net purchases and work done by other companies	-168,919,126	-188,559,371	-204,386,034	-184,290,556	-149,946,345	-178,285,332	-200,014,189	-216,554,961	-208,049,241	-209,122,966	-159,416
V. Changes in goods and prime materials	1,066,200	850,409	877,169	-337,178	-1,476,131	2,224,162	5,327	-783,816	-931,262	115,659	58
VI. Personal expenses	-35,106,784	-37,428,539	-38,548,441	-35,198,240	-37,364,198	-37,044,156	-38,741,755	-41,036,224	-39,011,730	-39,943,167	-28,177
VII. Other operating expenses	-36,329,775	-39,809,115	-42,721,509	-38,846,948	-38,429,759	-41,069,922	-43,065,627	-46,703,283	-46,498,485	-46,907,358	-36,662
EBITDA	**34,090,963**	**38,285,761**	**44,390,587**	**49,548,143**	**39,506,301**	**46,014,438**	**48,474,222**	**53,879,624**	**49,408,930**	**50,663,450**	**44,167**
VIII. Impairment and gains/losses on disposals of non-current assets	1,245,379	877,009	-1,252,108	-4,170,533	-358,671	-612,143	4,093,597	-3,358,575	-2,055,164	5,608,800	-3,063
IX. Amortization and depreciation charges on non-current assets and provisions surpluses	-9,340,325	-9,781,516	-9,844,172	-9,447,100	-9,838,149	-9,299,501	-9,133,147	-10,441,102	-9,261,447	-9,369,476	-7,180
PROFIT/LOSS FROM OPERATIONS (EBIT)	**14,220,835**	**15,055,187**	**15,884,058**	**5,460,487**	**4,411,414**	**8,406,858**	**12,685,156**	**4,080,939**	**5,574,587**	**15,492,979**	**8,296**
I. Financial income	3,097,150	3,491,773	3,797,533	5,340,781	4,212,397	4,054,566	5,271,251	5,779,873	4,377,435	3,888,587	2,453
II. Financial expenses	2,834,418	3,517,670	4,759,379	4,902,809	4,047,220	3,807,083	4,219,799	4,289,290	3,250,627	3,229,493	2,010
III. Change in fair value of financial instruments	-1,330,981	-919,923	-639,833	-1,573,152	-4,814,290	4,739	-54,990	-503,459	-760,908	-67,081	-434
NET FINANCIAL INCOME/EXPENSE	**-1,068,249**	**-945,820**	**-1,601,680**	**-1,135,179**	**-4,649,113**	**252,221**	**996,461**	**987,124**	**365,901**	**592,014**	**9**
PROFIT/LOSS BEFORE TAX	**13,152,587**	**14,109,367**	**14,282,378**	**4,325,308**	**-237,698**	**8,659,080**	**13,681,617**	**5,068,063**	**5,940,488**	**16,084,993**	**8,305**
Income tax	3,532,377	3,336,442	4,032,740	715,206	-691,244	1,784,186	1,758,545	1,933,318	1,422,714	2,464,949	1,892
PROFIT/LOSS OF THE YEAR	256,327,848	283,493,088	305,664,408	272,688,183	238,579,013	265,720,352	291,431,030	316,674,702	306,012,714	309,978,654	238,117

Appendix 2.A. Financial ratios construction sector

Liquidity Ratios		**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Current Ratio	$\frac{\text{Current Assets}}{\text{Current Liabilities}}$	1.65	1.72	1.87	1.83	2.17	2.17	2.20	2.14	2.19	2.20	2.22
Quick Ratio	$\frac{\text{Cash equivalents} + \text{FI} + \text{accounts receivables}}{\text{Current Liabilities}}$	0.79	0.80	0.78	0.82	0.80	0.83	0.84	0.85	0.84	0.89	0.91
Cash Ratio	$\frac{\text{Cash equivalents} + \text{FI}}{\text{Current Liabilities}}$	0.30	0.30	0.28	0.34	0.38	0.39	0.40	0.42	0.43	0.45	0.47
Working Capital to Total Assets Ratio	$\frac{\text{Current Assets} - \text{Current Liabilities}}{\text{Total Assets}}$	0.27	0.29	0.33	0.31	0.37	0.36	0.35	0.32	0.33	0.33	0.33

Leverage Ratios		**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Debt Ratio	$\frac{\text{Total Liabilities}}{\text{Total Equity and Liabilities}}$	0.68	0.69	0.69	0.68	0.67	0.65	0.63	0.59	0.58	0.55	0.54
Debt to Equity Ratio	$\frac{\text{Total Liabilities}}{\text{Equity}}$	2.08	2.18	2.26	2.12	2.07	1.83	1.68	1.46	1.36	1.24	1.18

Profitability Ratios		**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Return on Assets (%)	$\frac{\text{Net Income}}{\text{Total Assets}}$	2.82%	2.96%	2.07%	0.25%	-0.43%	-0.90%	-1.68%	-2.15%	-1.25%	-0.52%	-0.11%
Return on Equity (%)	$\frac{\text{Net Income}}{\text{Equity}}$	8.68%	9.39%	6.73%	0.77%	-1.33%	-2.56%	-4.49%	-5.28%	-2.94%	-1.17%	-0.23%

Efficiency Ratios		**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Stock Period (days)	$\frac{\text{Stocks} \times 365}{\text{Cosumption}}$	8,651.23	8,965.42	16,133.58	2,990.86	4,099.76	5,437.57	6,936.25	7,727.89	11,333.79	8,914.76	9,719.22
Average collection period (days)	$\frac{\text{Receivables} \times 365}{\text{Revenue}}$	123.49	128.26	135.49	118.60	136.54	149.82	161.48	169.92	184.47	172.15	153.11
Average payment period (days)	$\frac{\text{Payables} \times 365}{\text{Expenses and purchases}}$	220.12	222.73	238.59	206.01	271.19	291.90	300.22	322.81	354.60	324.73	289.38

Appendix 2.B. Financial ratios industrial sector

Liquidity Ratios		**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Current Ratio	$\frac{\text{Current Assets}}{\text{Current Liabilities}}$	1.17	1.19	1.20	1.18	1.18	1.28	1.27	1.32	1.33	1.34	1.38
Quick Ratio	$\frac{\text{Cash equivalents } + \text{ FI} + \text{ accounts receivables}}{\text{Current Liabilities}}$	0.86	0.87	0.88	0.85	0.87	0.94	0.93	0.96	0.97	0.98	1.04
Cash Ratio	$\frac{\text{Cash equivalents } + \text{ FI}}{\text{Current Liabilities}}$	0.24	0.23	0.25	0.27	0.29	0.31	0.31	0.32	0.33	0.33	0.36
Working Capital to Total Assets Ratio	$\frac{\text{Current Assets} - \text{Current Liabilities}}{\text{Total Assets}}$	0.08	0.09	0.09	0.07	0.08	0.11	0.10	0.12	0.13	0.13	0.14

Leverage Ratios		**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Debt Ratio	$\frac{\text{Total Liabilities}}{\text{Total Equity and Liabilities}}$	0.63	0.63	0.64	0.62	0.62	0.60	0.59	0.59	0.59	0.59	0.58
Debt to Equity Ratio	$\frac{\text{Total Liabilities}}{\text{Equity}}$	0.59	0.58	0.55	0.62	0.61	0.67	0.69	0.69	0.69	0.71	0.72

Profitability Ratios		**2005**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**
Return on Assets (%)	$\frac{\text{Net Income}}{\text{Total Assets}}$	4.28%	4.37%	3.77%	1.39%	0.16%	2.22%	3.75%	0.96%	1.55%	4.67%	2.98%
Return on Equity (%)	$\frac{\text{Net Income}}{\text{Equity}}$	11.50%	11.92%	10.59%	3.63%	0.42%	5.54%	9.23%	2.34%	3.81%	11.29%	7.13%

Efficiency Ratios		**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Stock Period (days)	$\frac{\text{Stocks} \times 365}{\text{Cosumption}}$	-969.44	-887.16	-791.95	-399.40	-514.48	-526.84	-494.74	-442.11	-458.64	-462.90	382.16
Average collection period (days)	$\frac{\text{Receivables} \times 365}{\text{Revenue}}$	90.11	91.72	89.48	81.24	103.16	101.65	95.03	91.32	88.04	87.32	85.01
Average payment period (days)	$\frac{\text{Payables} \times 365}{\text{Expenses and purchases}}$	127.71	126.22	125.00	121.76	154.04	139.40	131.07	121.69	118.92	116.54	109.30

Appendix 3.A. Profit and loss analysis construction sector

	% On Revenue										
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Revenue	100	100	100	100	100	100	100	100	100	100	100
Consumptions	1.46	1.17	0.89	4.58	8.82	10.33	7.17	8.00	4.23	5.55	4.78
GROSS MARGIN	**98.54**	**98.83**	**99.11**	**95.42**	**91.18**	**89.67**	**92.83**	**92.00**	**95.77**	**94.45**	**95.22**
Other operating income	2.38	2.25	2.65	1.59	2.30	2.62	3.14	3.50	3.80	3.56	3.29
Personal expenses	24.26	24.05	24.33	28.22	29.18	30.29	32.95	33.55	34.67	32.76	32.00
Other operating expenses	67.19	67.36	67.40	62.24	58.28	58.06	61.38	61.84	63.76	62.02	61.68
EBITDA	**9.46**	**9.66**	**10.03**	**6.56**	**6.03**	**3.94**	**1.64**	**0.11**	**1.15**	**3.24**	**4.83**
Amortization and depreciation	2.58	2.46	2.88	2.69	3.22	3.35	3.77	4.03	4.02	3.27	2.93
Impairment	-1.11	-1.30	-0.86	-0.08	0.08	0.34	0.96	1.14	0.95	0.60	0.38
EBIT	**8.00**	**8.50**	**8.01**	**3.94**	**2.72**	**0.25**	**-3.09**	**-5.06**	**-3.82**	**-0.64**	**1.51**
Financial income	1.02	1.21	1.36	0.95	1.49	1.34	1.65	1.40	2.30	2.07	1.37
Financial expenses	2.07	2.38	3.57	3.68	4.94	4.12	4.62	4.65	3.90	3.02	2.43
EBT	**6.94**	**7.34**	**5.80**	**1.22**	**-0.72**	**-2.53**	**-6.07**	**-8.31**	**-5.42**	**-1.59**	**0.46**
Income tax	2.20	2.27	1.71	0.76	0.50	0.25	-0.20	-0.07	0.05	0.48	0.83
PROFIT/LOSS OF THE YEAR	**4.74**	**5.07**	**4.08**	**0.46**	**-1.22**	**-2.78**	**-5.87**	**-8.23**	**-5.47**	**-2.07**	**-0.37**

Appendix 3.B. Profit and loss analysis industrial sector

	% On Revenue										
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Revenue	100	100	100	100	100	100	100	100	100	100	100
Consumptions	3.85	4.39	5.01	10.79	10.77	9.56	9.51	11.00	10.42	9.96	10.41
GROSS MARGIN	**96.15**	**95.61**	**94.99**	**89.21**	**89.23**	**90.44**	**90.49**	**89.00**	**89.58**	**90.04**	**89.59**
Other operating income	1.32	1.25	1.31	1.47	1.70	1.69	1.75	1.62	1.55	1.48	1.59
Personal expenses	13.70	13.20	12.61	12.91	15.66	13.94	13.29	12.96	12.75	12.89	11.83
Other operating expenses	75.06	75.20	74.86	70.78	69.14	71.29	72.86	72.01	72.86	72.43	71.56
EBITDA	**8.71**	**8.45**	**8.83**	**7.00**	**6.12**	**6.89**	**6.08**	**5.65**	**5.52**	**6.21**	**7.79**
Amortization and depreciation	3.64	3.45	3.22	3.46	4.12	3.50	3.13	3.30	3.03	3.02	3.02
Impairment	-0.49	-0.31	0.41	1.53	0.15	0.23	-1.40	1.06	0.67	-1.81	1.29
EBIT	**5.55**	**5.31**	**5.20**	**2.00**	**1.85**	**3.16**	**4.35**	**1.29**	**1.82**	**5.00**	**3.48**
Financial income	0.69	0.91	1.03	1.38	-0.25	1.53	1.79	1.67	1.18	1.23	0.85
Financial expenses	1.11	1.24	1.56	1.80	1.70	1.43	1.45	1.35	1.06	1.04	0.84
EBT	**5.13**	**4.98**	**4.67**	**1.59**	**-0.10**	**3.26**	**4.69**	**1.60**	**1.94**	**5.19**	**3.49**
Income tax	1.38	1.18	1.32	0.26	-0.29	0.67	0.60	0.61	0.46	0.80	0.79
PROFIT/LOSS OF THE YEAR	**3.75**	**3.80**	**3.35**	**1.32**	**0.19**	**2.59**	**4.09**	**0.99**	**1.48**	**4.39**	**2.69**

Appendix 4. Results and accuracy of the models the years prior to bankruptcy

- Altman model

2 YEARS BEFORE				
Observed	Forecasted			Correct %
	Safe	Distress	Grey	
Safe	85	26	31	59.86%
Distress	48	30	63	44.68%
Accuracy of the model				**52.30%**

Note: it was not possible to apply the model to 6 of the solvent companies and 7 of the insolvent ones.

3 YEARS BEFORE				
Observed	Forecasted			Correct %
	Safe	Distress	Grey	
Safe	75	23	37	55.56%
Distress	54	23	56	42.11%
Accuracy of the model				**48.88%**

Note: it was not possible to apply the model to 13 of the solvent companies and 15 of the insolvent ones.

4 YEARS BEFORE				
Observed	Forecasted			Correct %
	Safe	Distress	Grey	
Safe	73	27	29	56.59%
Distress	56	22	44	36.07%
Accuracy of the model				**46.61%**

Note: it was not possible to apply the model to 19 of the solvent companies and 26 of the insolvent ones.

5 YEARS BEFORE				
Observed	Forecasted			Correct %
	Safe	Distress	Grey	
Safe	80	19	28	62.99%
Distress	52	22	40	35.09%
Accuracy of the model				**49.79%**

Note: it was not possible to apply the model to 21 of the solvent companies and 34 of the insolvent ones.

- Ohlson model

2 YEARS BEFORE			
Observed	Forecasted		Correct %
	Safe	Distress	
Safe	59	84	41.26%
Distress	18	125	87.41%
Accuracy of the model			**64.34%**

Note: it was not possible to apply the model to 5 of the solvent companies and 5 of the insolvent ones.

3 YEARS BEFORE			
Observed	Forecasted		Correct %
	Safe	Distress	
Safe	51	85	37.50%
Distress	19	114	85.71%
Accuracy of the model			**61.34%**

Note: it was not possible to apply the model to 12 of the solvent companies and 15 of the insolvent ones.

4 YEARS BEFORE			
Observed	Forecasted		Correct %
	Safe	Distress	
Safe	53	78	40.46%
Distress	16	105	86.78%
Accuracy of the model			**62.70%**

Note: it was not possible to apply the model to 17 of the solvent companies and 27 of the insolvent ones.

5 YEARS BEFORE			
Observed	Forecasted		Correct %
	Safe	Distress	
Safe	53	74	41.73%
Distress	20	94	82.46%
Accuracy of the model			**61.00%**

Note: it was not possible to apply the model to 21 of the solvent companies and 34 of the insolvent ones.

- Ismail model

2 YEARS BEFORE			
Observed	Forecasted		Correct %
	Safe	Distress	
Safe	71	71	50.00%
Distress	51	91	64.08%
Accuracy of the model			**57.04%**

Note: it was not possible to apply the model to 6 of the solvent companies and 6 of the insolvent ones.

3 YEARS BEFORE			
Observed	Forecasted		Correct %
	Safe	Distress	
Safe	65	69	48.51%
Distress	46	83	64.34%
Accuracy of the model			**56.27%**

Note: it was not possible to apply the model to 14 of the solvent companies and 19 of the insolvent ones.

4 YEARS BEFORE			
Observed	Forecasted		Correct %
	Safe	Distress	
Safe	60	67	47.24%
Distress	45	71	61.21%
Accuracy of the model			**53.91%**

Note: it was not possible to apply the model to 21 of the solvent companies and 32 of the insolvent ones.

5 YEARS BEFORE			
Observed	Forecasted		Correct %
	Safe	Distress	
Safe	63	60	51.22%
Distress	41	65	38.68%
Accuracy of the model			**55.90%**

Note: it was not possible to apply the model to 25 of the solvent companies and 42 of the insolvent ones.

Appendix 5. SPSS report

Regresión logística

[ConjuntoDatos1]

Resumen de procesamiento de casos

Casos sin ponderar[a]		N	Porcentaje
Casos seleccionados	Incluido en el análisis	296	100,0
	Casos perdidos	0	,0
	Total	296	100,0
Casos no seleccionados		0	,0
Total		296	100,0

a. Si la ponderación está en vigor, consulte la tabla de clasificación para el número total de casos.

Codificación de variable dependiente

Valor original	Valor interno
0	0
1	1

Bloque 0: Bloque de inicio

Pruebas ómnibus de coeficientes de modelo

		Chi-cuadrado	gl	Sig.
Paso 1	Paso	181,673	9	,000
	Bloque	181,673	9	,000
	Modelo	181,673	9	,000

Resumen del modelo

Paso	Logaritmo de la verosimilitud -2	R cuadrado de Cox y Snell	R cuadrado de Nagelkerke
1	228,670[a]	,459	,612

a. La estimación ha terminado en el número de iteración 12 porque las estimaciones de parámetro han cambiado en menos de ,001.

Tabla de clasificación[a]

			Pronosticado		
			Solvencia		Porcentaje correcto
Observado			0	1	
Paso 1	Solvencia	0	121	27	81,8
		1	17	131	88,5
	Porcentaje global				85,1

a. El valor de corte es ,500

Variables en la ecuación

		B	Error estándar	Wald	gl	Sig.	Exp(B)
Paso 1[a]	Quickratio	,159	,117	1,848	1	,174	1,172
	ROA	,314	,694	,204	1	,651	1,368
	TLTA	-3,945	,888	19,737	1	,000	,019
	Current	-,007	,021	,109	1	,741	,993
	WCTA	-,482	,612	,620	1	,431	,618
	AverageDaysSalesOutstanding	-,003	,001	13,428	1	,000	,997
	retainedearningstototalassets	-,047	,078	,355	1	,551	,954
	earningsbeforeinterestandtaxestototalassets	1,302	1,159	1,262	1	,261	3,676
	equitytototaldebt	,215	,139	2,381	1	,123	1,240
	Constante	3,719	,790	22,160	1	,000	41,229

a. Variables especificadas en el paso 1: Quickratio, ROA, TLTA, Current, WCTA, AverageDaysSalesOutstanding, retainedearningstototalassets, earningsbeforeinterestandtaxestototalassets, equitytototaldebt.

Bloque 1: Método = Entrar

Pruebas ómnibus de coeficientes de modelo

		Chi-cuadrado	gl	Sig.
Paso 1	Paso	159,490	2	,000
	Bloque	159,490	2	,000
	Modelo	159,490	2	,000

Resumen del modelo

Paso	Logaritmo de la verosimilitud -2	R cuadrado de Cox y Snell	R cuadrado de Nagelkerke
1	250,853[a]	,417	,555

a. La estimación ha terminado en el número de iteración 11 porque las estimaciones de parámetro han cambiado en menos de ,001.

Tabla de clasificación[a]

Observado			Pronosticado		
			Solvencia		Porcentaje correcto
			0	1	
Paso 1	Solvencia	0	116	32	78,4
		1	23	125	84,5
	Porcentaje global				81,4

a. El valor de corte es ,500

Variables en la ecuación

		B	Error estándar	Wald	gl	Sig.	Exp(B)
Paso 1[a]	TLTA	-4,954	,727	46,455	1	,000	,007
	AverageDaysSalesOutstanding	-,001	,000	12,974	1	,000	,999
	Constante	4,373	,605	52,324	1	,000	79,267

a. Variables especificadas en el paso 1: TLTA, AverageDaysSalesOutstanding.

Appendix 6.A. Minitab report first iteration

Multiple Regression for Solvency
Model Building Report

X1: TL/TA X2: Quick Ratio X3: NI/TA X4: Ret. Earn./T X5: Equity/TL

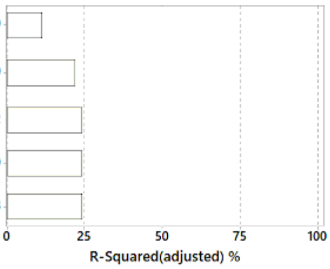
Final Model Equation

Solvency = 0,8073 - 0,3995 X1 + 0,01547 X2 - 0,0368 X3 + 0,02386 X1^2 + 0,1568 X2*X3

Model Building Sequence

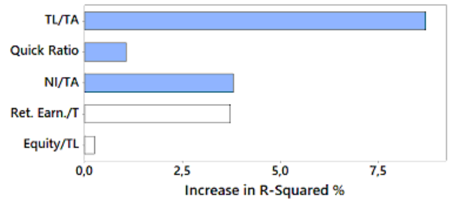
Displays the order in which terms were added or removed.

Step	Change	Step P	Final P
1	Add X1	0,000	0,000
2	Add X1^2	0,000	0,000
3	Add X2	0,082	0,082
	Add X3	0,020	0,020
	Add X2*X3	0,008	0,008



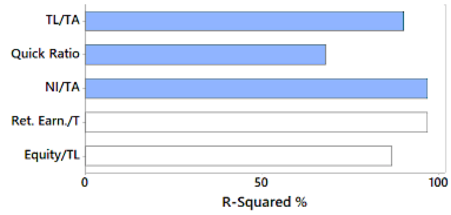
Incremental Impact of X Variables

Long bars represent Xs that contribute the most new information to the model.



Each X Regressed on All Other Terms

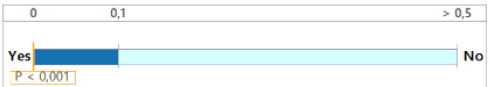
Gray bars represent Xs that do not help explain additional variation in Y.



A gray bar represents an X variable not in the model.

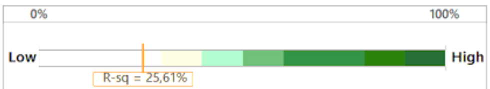
Multiple Regression for Solvency
Summary Report

Is there a relationship between Y and the X variables?



The relationship between Y and the X variables in the model is statistically significant (p < 0,10).

% of variation explained by the model



25,61% of the variation in Y can be explained by the regression model.

Comments

The following terms are in the fitted equation that models the relationship between Y and the X variables:
X1: TL/TA
X2: Quick Ratio
X3: NI/TA
X1^2; X2*X3

If the model fits the data well, this equation can be used to predict Solvency for specific values of the X variables, or find the settings for the X variables that correspond to a desired value or range of values for Solvency.

Appendix 6.B. Minitab report final model

Multiple Regression for Solvency
Model Building Report

X1: TL/TA X2: Quick Ratio X3: NI/TA X4: Ret. Earn./T X5: Ave. Days ou

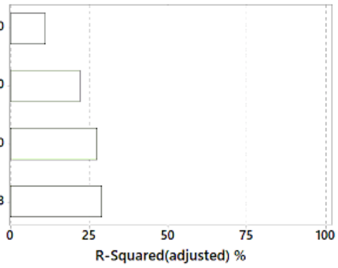
Final Model Equation

Solvency = 0,9475 - 0,4021 X1 - 0,000724 X5 + 0,02729 X1^2 + 0,000000 X5^2

Model Building Sequence

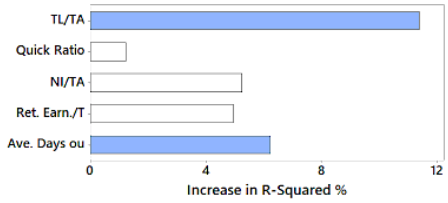
Displays the order in which terms were added or removed.

Step	Change	Step P	Final P
1	Add X1	0,000	0,000
2	Add X1^2	0,000	0,000
3	Add X5	0,000	0,000
4	Add X5^2	0,008	0,008



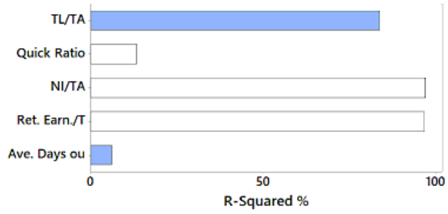
Incremental Impact of X Variables

Long bars represent Xs that contribute the most new information to the model.



Each X Regressed on All Other Terms

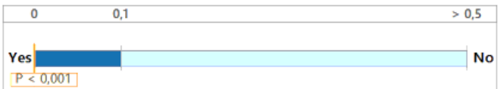
Gray bars represent Xs that do not help explain additional variation in Y.



A gray bar represents an X variable not in the model.

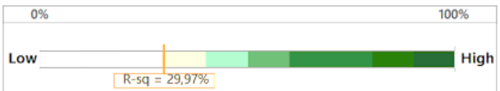
Multiple Regression for Solvency
Summary Report

Is there a relationship between Y and the X variables?



The relationship between Y and the X variables in the model is statistically significant (p < 0,10).

% of variation explained by the model



29,97% of the variation in Y can be explained by the regression model.

Comments

The following terms are in the fitted equation that models the relationship between Y and the X variables:
X1: TL/TA
X5: Ave. Days outs.
X1^2; X5^2

If the model fits the data well, this equation can be used to predict Solvency for specific values of the X variables, or find the settings for the X variables that correspond to a desired value or range of values for Solvency.

Appendix 7. Results and accuracy of the proposed models the years prior to bankruptcy

- SPSS model

2 YEARS BEFORE			
Observed	Forecasted		Correct %
	Safe	Distress	
Safe	91	51	64.08%
Distress	39	103	72.54%
Accuracy of the model			68.31%

Note: it was not possible to apply the model to 6 of the solvent companies and 6 of the insolvent ones.

3 YEARS BEFORE			
Observed	Forecasted		Correct %
	Safe	Distress	
Safe	88	46	65.67%
Distress	37	93	71.54%
Accuracy of the model			68.56%

Note: it was not possible to apply the model to 14 of the solvent companies and 18 of the insolvent ones.

4 YEARS BEFORE			
Observed	Forecasted		Correct %
	Safe	Distress	
Safe	78	49	61.42%
Distress	35	81	69.83%
Accuracy of the model			65.43%

Note: it was not possible to apply the model to 21 of the solvent companies and 32 of the insolvent ones.

5 YEARS BEFORE			
Observed	Forecasted		Correct %
	Safe	Distress	
Safe	83	40	67.48%
Distress	30	76	28.30%
Accuracy of the model			69.43%

Note: it was not possible to apply the model to 25 of the solvent companies and 42 of the insolvent ones.

- Minitab model

2 YEARS BEFORE			
Observed	Forecasted		Correct %
	Safe	Distress	
Safe	111	31	78.17%
Distress	70	72	50.70%
Accuracy of the model			64.44%

Note: it was not possible to apply the model to 6 of the solvent companies and 6 of the insolvent ones.

3 YEARS BEFORE			
Observed	Forecasted		Correct %
	Safe	Distress	
Safe	100	34	74.63%
Distress	68	62	47.69%
Accuracy of the model			61.36%

Note: it was not possible to apply the model to 14 of the solvent companies and 18 of the insolvent ones.

4 YEARS BEFORE			
Observed	Forecasted		Correct %
	Safe	Distress	
Safe	102	25	80.31%
Distress	61	55	47.41%
Accuracy of the model			64.61%

Note: it was not possible to apply the model to 21 of the solvent companies and 32 of the insolvent ones.

5 YEARS BEFORE			
Observed	Forecasted		Correct %
	Safe	Distress	
Safe	96	27	78.05%
Distress	63	43	59.43%
Accuracy of the model			60.70%

Note: it was not possible to apply the model to 25 of the solvent companies and 42 of the insolvent ones.

Appendix 8. Results and accuracy of the proposed models the years prior to bankruptcy in the companies outside the initial sample

- SPSS model

2 YEARS BEFORE			
Observed	Forecasted		Correct %
	Safe	Distress	
Safe	8	2	80.00%
Distress	1	9	90.00%
Accuracy of the model			**85.00%**

3 YEARS BEFORE			
Observed	Forecasted		Correct %
	Safe	Distress	
Safe	8	1	88.89%
Distress	2	8	80.00%
Accuracy of the model			**84.21%**

Note: it was not possible to apply the model to 1 of the solvent companies.

4 YEARS BEFORE			
Observed	Forecasted		Correct %
	Safe	Distress	
Safe	5	3	62.50%
Distress	1	7	87.50%
Accuracy of the model			**75.00%**

Note: it was not possible to apply the model to 2 of the solvent companies and 2 of the insolvent ones.

5 YEARS BEFORE			
Observed	Forecasted		Correct %
	Safe	Distress	
Safe	4	4	50.00%
Distress	1	6	85.71%
Accuracy of the model			**66.67%**

Note: it was not possible to apply the model to 2 of the solvent companies and 3 of the insolvent ones.

- Minitab model

2 YEARS BEFORE			
Observed	Forecasted		Correct %
	Safe	Distress	
Safe	7	2	77.78%
Distress	4	6	60.00%
Accuracy of the model			**68.42%**

3 YEARS BEFORE			
Observed	Forecasted		Correct %
	Safe	Distress	
Safe	7	2	77.78%
Distress	7	3	30.00%
Accuracy of the model			**52.63%**

Note: it was not possible to apply the model to 1 of the solvent companies.

4 YEARS BEFORE			
Observed	Forecasted		Correct %
	Safe	Distress	
Safe	7	1	87.50%
Distress	4	4	50.00%
Accuracy of the model			**68.75%**

Note: it was not possible to apply the model to 2 of the solvent companies and 2 of the insolvent ones.

5 YEARS BEFORE			
Observed	Forecasted		Correct %
	Safe	Distress	
Safe	3	5	37.50%
Distress	2	5	71.43%
Accuracy of the model			**53.33%**

Note: it was not possible to apply the model to 2 of the solvent companies and 3 of the insolvent ones.