Does the macroeconomic context condition the prediction of business failure?

¿Condiciona el contexto macroeconómico a la predicción de quiebra empresarial?

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Abstract

The objective of this study is to identify both micro and macroeconomic variables that allow us to analyze in advance the probabilities of business failure. The selected sample contains all the listed companies of the IPC index of Mexico, IBEX-35 of Spain and EURO STOXX50 of Europe for a time horizon of 5 years. Our contribution lies in the empirical testing of the results by two different techniques: general estimating equations (a parametric technique) and a decision tree (a non-parametric technique based on artificial intelligence). The obtained results show that the factors of liquidity, indebtedness and profitability are the ones that affect the prediction of corporate bankruptcy for listed companies, but not the macroeconomic ones, since the macroeconomic peculiarities of each country are diluted by the importance of the economic-financial structure of each company.

Business bankruptcy, Macroeconomics variables, Panel data models, Decision tree

Resumen

El objetivo de este estudio es identificar aquellas variables tanto micro como macroeconómicas que permitan analizar anticipadamente las probabilidades de fracaso empresarial. La muestra utilizada fue de la totalidad de empresas cotizadas de los índices IPC de México, IBEX-35 de España y EURO STOXX50 de Europa para un horizonte temporal de 5 años. Nuestra contribución radica en la contrastación empírica de los resultados mediante dos técnicas distintas: ecuaciones de estimación generalizadas (técnica paramétrica) y el árbol de decisión (técnica no paramétrica de Inteligencia Artificial). Dichos resultados son que los factores de liquidez, endeudamiento y rentabilidad son los que afectan a la predicción de quiebra empresarial para empresas cotizadas y no los macroeconómicos, ya que las particularidades macroeconómicas de cada país se diluyen por la importancia de la estructura económico-financiera de cada empresa.

Quiebra empresarial, Variables macroeconómicas, Modelos de datos de panel, Árbol de decisión

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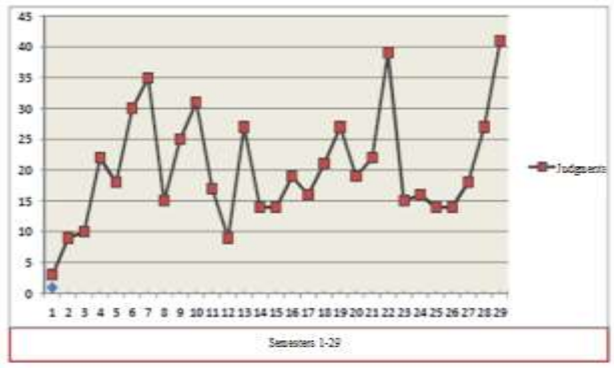
Introduction

The development and use of models for predicting companies in financial difficulties have been the subject of a multitude of studies at least in the last five decades, mainly due to the very negative consequences that business failures have for society in general and for the economy in particular. After more than seventy years of trying to study why companies fail and more than fifty years of modeling the behaviour of companies with financial problems compared to those without, there is still no single, clear theory of business failure (Lukason, 2016). In fact, every time there is an economic crisis there seems to be an increase in studies on the subject. In 1966, when Beaver's first empirical study was published, 9 articles were published in the Web of Knowledge (ISI), the first database of prestigious articles worldwide. The number of articles on bankruptcy has reached 818 in 2017.[1]

In addition, Korol (2013) states that business problems are not sudden. On the contrary, the appeared five to six years before they enter in the bankruptcy procedure, so they have to be predictable or at least explainable. The economic problem that a company can have in such a situation is very serious and that is the reason why having prediction models that allow us to identify possible difficulties is of great importance for entrepreneurs, managers, shareholders, investors as well as for researchers.

Although this is true, what is even more interesting is to be able to take the necessary actions avoiding consequences that imply greater losses. Many companies go bankrupt as a result of economic crises. For example, in Mexico for the last 10 years, 468 companies from all sectors have been in insolvency in the country. The director of IFECOM in Mexico said that as an immediate effect of an economic crisis there is an increase in litigation between companies. This was the case with companies such as "Comercial Mexicana", which in 2008 began to have problems with the banks with whom it contracted derivative financial instruments to supposedly improve their finances (Contreras, Segovia-Vargas and Camacho, 2014).

As can be seen in Graph 1, the number of companies that enter into insolvency proceedings in Mexico increases during periods of economic crisis. For example, in 2010 (global economic crisis) and 2014 (currency depreciation).



Graph 1 Evolution of the number of companies in bankruptcy procedure in Mexico
Source: IFECOM Work Report June-November 2014

Another example can be found in Spain, where the number of companies that have gone bankrupt in recent years has risen to almost 10,000 companies. Comparing this figure with the years before the crisis, the trend has multiplied by 100. In fact, the global index "Euler-Hermes" on the insolvency of countries, for Spain in 2012, the worst post-crisis period, suffered an increase of 32% over 2011, while the average of the euro area remained around 7%. In the same period, the indicator for Mexico was 23%. This fact is relevant because it is assumed that the social stigma of the insolvency proceedings penalizes companies that enter the legal process and those that enter, is because they are really in a situation of "induced coma", which means that 9 out of 10 of these companies end up in liquidation and not financially reorganized to return to the market (Camacho-Miñano, Segovia-Vargas and Pascual-Ezama, 2015; Segovia-Vargas and Camacho-Miñano, 2018).

These microeconomic data are also reflected at the macroeconomic level. For example, in the growth of gross domestic product (GDP), the unemployment rate, public debt or the risk of credit insolvency. The following graph (Graph 2) shows the trend of the interannual variation of GDP, the unemployment rate and the public debt in the case of Spain and Mexico as well as the figures to buy with the average of the Eurozone.

[1] Using the keyword "bankruptcy"

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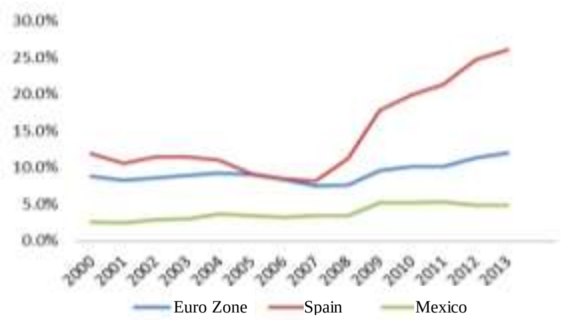
The year-on-year variation in GDP shows a sharp drop in this macroeconomic indicator in 2009, both in Spain and in the rest of the Eurozone, a year of the strong impact of the economic crisis. This is due, to a large extent, to the closure of many companies to the economic recession suffered in that period.

GDP
Unemployment



Graph 2 Year-on-year change in GDP and unemployment in Spain, Mexico and the Eurozone
Source: World Bank (www.datos.bancomundial.org)

In 2009 it was also observed that the trend in the unemployment rate rose to 26% in Spain. On the same date, the unemployment rate was 12% in the Eurozone as a whole.

With respect to public debt, there is also a growth in the weight of debt reaching, at the end of 2013, 92.1% of GDP in Spain and almost 90.9% in the Euro Zone, while in Mexico has maintained a growth of more than 3 percentage points since 2012 passing from 43.17% and reaching levels of 50.08% by the end of 2014, according to World Bank data.

These macroeconomic variables analyzed are only a few examples, but the reality is that there are many others that are affected in periods of economic recession and could be used to predict business failure. Similarly, country legislation also affects. For example, the resolution of business failure situations is different depending on the country involved.

This has been demonstrated by comparing different countries within the European Union (Weijs, 2012). In fact, there are economic studies that justify how laws on corporate insolvency can condition the development of entrepreneurship in a country (Lee et al., 2011), national economic growth (Laporta et al., 1998), economic stability (Beraho and Elisu, 2010) and even the development of stock markets (Levine, 1998). It is also empirically verified how one bankruptcy law or another can change foreign investments in a country (Pindado, Rodriguez and de la Torre, 2008). Hence, the correct development of insolvency laws is of vital importance to promoting economic growth and legal certainty for investors.

In view of the above, the objective of this study is to analyze whether or not macroeconomic variables can improve the predictive power of traditional bankruptcy prediction models. Since the listed companies are supposed to reflect the daily life of each country, sector, and company, we are going to use a sample of these companies in the most relevant world indices. It is assumed that new macroeconomic variables could improve models based only on accounting variables.

The specific objective is to contrast or compare the results obtained through the empirical application of two different techniques in order to analyze the robustness of our conclusions. On the one hand, parametric techniques belonging to multivariate statistical analysis are used, such as generalized estimation equations (GEE) and, on the other hand, non-parametric techniques belonging to artificial intelligence (AI) such as decision trees applied to a sample of panel data (Tinoco, Venegas and Torres, 2018).

The article is structured as follows: Section 2 contains the literature review. Next, section 3 includes the hypotheses of the research, the description of the sample and the variables and the methodologies used. In the following section, we present the results and the last section presents the conclusions.

Literature Review

Over the years, many researchers have focused their efforts on trying to determine the level of solvency of a business in order to predict or avoid the bankruptcy of a company through the use of ratios, statistical methods and financial analysis on factors that directly impact liquidity, leverage, and profitability, among others. In 1932 Fitzpatrick carried out the first works giving rise to what is known as the descriptive stage. His primary objective was to try to detect business failures through the use of ratios only. In the same line is the work of Winakor and Smith (1935), applying basic univariate analysis techniques, analyzing the trends of various financial ratios. However, it was not until the 1960s that more complex statistical techniques such as discriminant, univariate and multiple analysis began to be used. Based on these studies, Beaver (1966), Altman (1968) and many others have attempted to develop a general theory of business failure, albeit still unsuccessful. In these studies, the methodology is based on a paired design of companies.

Initially, studies that attempted to predict and therefore explain business failure were based on ratios derived from accounting information (Ohlson, 1980). They consisted of analyzing the cases of real business failures and, using an inductive method, learning the common characteristics of failed companies by comparing them with "healthy" companies. However, even today, with more than half a century of subsequent research, there is still no unanimity among researchers as to which accounting ratios best explain the insolvency situation. In the accounting literature, many researchers have used key ratios from financial analysis or financial statement documents (balance sheet, profit and loss account, or cash flow statement) to explain bankruptcy (Altman et al., 2017). Generally speaking, there are three types of ratios most used by academics on the subject: profitability ratios, debt ratios and economic-financial equilibrium ratios (among others, see: Tascón Fernández and Castaño Gutiérrez (2012); Korol (2013)). The relationship between profitability and liquidity seems logical since the idea is that companies with financial problems are less able to access financing, external financial resources, such as banks, which means significant cash imbalances.

Depending on the methodology used in forecasting insolvencies, the way in which explanatory factors are selected may vary. In other words, if traditional statistical techniques are used, the way in which the variables explaining the sample are selected may condition the results, as not all existing accounting ratios can be included due to problems of multicollinearity between them. In addition, variables are also required to meet certain baseline assumptions, such as the criteria of normality and heteroscedasticity, in order to be able to apply certain statistical techniques.

In the decade of the 80's the first questionings to these last models appear because they are not random Zmijewski (1984) and because of the advances in the methodology with logistic regression or Logit model. Motivated by the importance of incorporating the history of each company, we began with the application of models for longitudinal data, such as the mixed linear model or the mixed logistic model, which incorporate in their analysis the financial statements of each company in a time horizon. At the time of elaborating this type of models, it is also relevant to the selection of the variables to use. Different techniques are used for this: main components, degree of statistical significance of the variables (forward or backward), the judgment of researchers or professionals, cluster analysis, etc.

If it is decided to use non-traditional methodologies (De Andrés, Landajo and Lorca., 2012; Du Jardin, 2018; Ravi Kumar and Ravi, 2007) as artificial intelligence methods (rough set, decision trees such as PART algorithms, C4.5, random forest, neural networks...), all available variables can be considered as long as they classify the problem to be studied well, i.e. that its level of significance is acceptable. However, although errors in the classification of failed enterprises have been reduced, they have not been fully classified. According to a study by Aziz and Dar (2006) up to that date, studies predicting the risk of insolvency had used statistical models in 64% of the cases, 25% had made use of soft computing techniques or artificial intelligence, and 11% had studied the phenomenon through another one.

Regardless of the methodology used, accounting ratios involve a number of limitations inherent in accounting. First, accounting data are historical data, based on past events, which sometimes makes it difficult to make predictive decisions in the future (Yeh, Lin and Hsu, 2012). Another limitation of accounting data is that they are subject to manipulation or bias, depending on the incentives that their managers have: the lower payment of taxes, postponing or avoiding a legal insolvency process, showing a healthy image to get credit, and so on. (Campa and Camacho-Miñano, 2014). In addition, the accounting policies of companies, and even the sectors to which they belong may have some influence on accounting variables (Balcaen and Ooghe, 2006). Likewise, whether or not they belong to a group of companies and the type of group could modify these variables (Korol, 2013).

Another problem is the existence of different accounting regulations, which makes it difficult to use data from companies worldwide. Finally, there are academic studies that highlight the role that accounting information plays on the probability of insolvency of companies (Meeks and Meeks, 2009), since the paradox is that the simple probability of insolvency affects the accounting valuation of assets and liabilities and that, in turn, the valuation of these conditions this probability.

Despite all these accounting problems, models with financial ratios (accounting data) are zrecognized and used worldwide. Thus, Agarwal and Taffler (2008); Das, Hanouna, and Sarin (2009) and Bauer and Argawal (2014) point out that, taking into account the profitability of models based on accounting data, market-based models and risk models prevail in the finance literature. For Argawal and Taffler (2008), there is little predictive difference between models based on accounting data and those based on the market, however, the use of models based on accounting allows a higher level of risk-adjusted return.

However, even though various types of research have been conducted related to predicting business failure, the original "Z-Score" model introduced by Altman (1968) has been the dominant and globally applicable model (Altman et al., 2017).

Although its origin is more than 45 years old, it is still used as a prediction tool in bankruptcies or financial difficulties.

Despite all the above, two options are considered to increase the predictive power of the models by researchers: either the use of stock market variables or the use of other non-financial variables. Marais, Patell, and Wolfson (1984) were the first to point out that stock prices improved the prediction of failure, compared to the use of accounting variables only. Barniv, Agarwal, and Leach (1997) found that there were accumulated abnormal results, weighted by market prices, before firms entered the contest. Hillegeist et al. (2004) noted that adding market variables to models improved information opportunity. In fact, Chava and Purnanandam (2010) found a positive relationship between stock returns and the risk of failure. A study by Bauer and Agarwal (2014) points out that hazard models add greater predictability than traditional models for predicting potential insolvencies. Other research has also focused on the predictive power of financial statements (Collins, Maydew, and Weiss, 1997; Francis and Shipper, 1999, among others).

With regard to non-financial variables, variables such as the age of the company since its foundation, size (such as algorithm of total assets, the average number of employees and sales figure) and sector (Tascón and Castaño, 2012) were added to the models.

Among the first studies that attempted to create a theory of business failure and success, the theory developed by Lussier (1995) stands out, based on fifteen internal variables of the company, such as the level of initial capitalisation of the business, the experience of the company in the sector or the training of managers. However, the main problem of this study was the difficulty in obtaining this type of data from failed companies, coming from interviews with managers. Many other variables have been added model by model. Thus, Laitinen and Laitinen (2009) incorporate information on audit reports, and De Andrés, Landajo and Lorca (2012), which make use of standards from different economic sectors. Other more specific audit report variables have also been added recently, such as the auditors' comments, which improve the practical power of the auditors.

Other more specific audit report variables have also been added recently, such as auditor comments, which improve the predictive power of Altman's models (Muñoz-Izquierdo, 2017).

Noga and Schnader (2013) use temporary tax differences, Kallunki and Pyykkö (2013) analyze the past experience of the managers of companies in competition and Chiu, Peña and Wang (2013) explain the probability of business failure depending on the degree of concentration of the sector, based on the idea that the more competition in a sector, the greater the probability of failure.

Finally, it should be noted that the latest trend in business failure investigations is cross-country comparisons. Few studies have carried out a comparative study mainly due to the lack of access to data from different countries. The development of international trade databases has led to these studies, although there is still a theory of business failure to be built. One of the first studies was that of Altman and Narayanan (1997). They reviewed business failure prediction models in 22 countries. Another study by Ravid and Sundgren (1998) compared the efficiency of Finnish and US legal codes governing business failure. Analyzing 70 companies from each country, they found that, although the economic factors affecting bankruptcy proceedings coincide in both countries, Finnish legislation favors a liquidation process to a greater extent than the American one, rather than achieving the reorganization of a company. Laitinen (2002) also analyzed companies from 17 European countries and the United States, concluding that there are differences between countries with regard to the degree of reliability of the models. On the basis of the analysis of their sample, the countries that obtained the highest degree of reliability in their classification were Germany, Belgium, Italy, Finland and Greece, and the lowest were Switzerland, Ireland, and Portugal.

Similarly, Bellovary, Giacomi, and Akers (2007) refer to models in 18 countries. Davydenko and Franks (2008), with a sample of approximately 1,500 companies from Germany, France and the United Kingdom, concluded that the legislation in force in each country affected business crises, although the role of banks or competition also affects the tendering of companies.

A study conducted by Korol (2013) compares data from Polish companies listed, healthy and in competition, with Latin American companies (from Mexico, Argentina, Peru, Brazil and Chile) using traditional methodologies and artificial intelligence.

He concludes that it is more difficult to explain the Latin American companies than the European ones since the normative and macroeconomic context of the Latin American ones conditions the competition. Another study by Laitinen and Suvas (2013) compares 30 European countries, pointing out that, despite the differences between countries, it is possible to predict business failure with some acceptable classification errors.

A recent study is the work of Altman et al. (2017). It stands out for an exhaustive review of the literature on the importance and effectiveness of Altman's Z-Score model for predicting global bankruptcy and its applications in bonds and other related areas.

The review is based on an analysis of 33 scientific articles published from 2000 to the present in the major financial and accounting journals. The result of the analysis shows that while a general international model works reasonably well, with predictive accuracy levels ranging from 75% to 90%, classification accuracy can be improved considerably with country-specific estimates, especially with the use of additional variables.

In short, the line of research on predicting bankruptcy between countries is key due to the globalization of international markets and the existence of a global investor.

Therefore, the existence of a common bankruptcy or failure prediction model for different countries with a high degree of reliability remains relevant and is one of the purposes of this thesis.

The research continues around the world in order to "perfect" predictive models with the addition in the application of both parametric and non-parametric techniques more efficient that have attempted to obtain greater accuracy in prediction.

Research hypotheses, sample, variables and methodologies

1. Research hypotheses

H_0: The presence of macroeconomic variables conditions business failure in a global context of listed companies. In other words, macroeconomic variables should increase the predictive power of models without taking these variables into account.

2. Sample

For the selection of the companies in this study, all the companies that made up the following reference indices without prior knowledge of their financial situation were used: IPC of Mexico (35 companies), IBEX35 of Spain (34 companies) and EURO STOXX 50 of the Eurozone (50 companies).

Therefore the sample is made up of 119 companies. The geographical unit refers to the selection of the region or country to which the units of analysis belong. In most of the investigations carried out, it has been chosen to include samples belonging to a single country or region, however, in this research the geographical unit has been extended to several countries considering the place where the companies carry out their economic activity.

The time unit comprises the time period of the database. Normally these periods are annual and vary from 3 to 10 years. In the present study, the accumulated data for the last quarter of each year from 2010 to 2014 were available, so there is a time horizon of 5 years.

3. Description of the variables

The determination of the dependent variable is a subject of multiple divergences and contradictions. The analysis of bankruptcy or business failure gives rise to disagreements due to the nation consensus in the definitions and to the timing and indicators that are used to declare such a state. Given that the factors that can cause business failure are many and of diverse nature, the intention of this paper will be to detect indications or indicators from the information contained in the financial statements.

Due to the problematic exposed, and before the diversity of definitions, in the present study we have classified the companies in two categories, healthy and bankruptcy, according to the score obtained when using the Z-score of Altman (1968), an indicator that continues valid for almost fifty years. Based on Altman's experience with companies in financial difficulties, an index was developed using five ratios and five weights, with the aim of forecasting the bankruptcy of listed manufacturing companies. The experience of this model led the author to conclude that Z-Score scores below 1.81 indicated a high probability of bankruptcy. On the other hand, scores above 3.00 indicated a low probability of bankruptcy. The range between 1.81 and 2.99 was referred to as the "ignorance zone". Companies with this Z-score should be analyzed in depth to determine their probability of bankruptcy. After applying this indicator to the 119 companies in the study and using information from their financial statements, we obtain a classification as shown in the following table (Table 1).

Year	Healthy firms	Bankrupt firms	Not-classified
2010	46	38	35
2011	43	45	31
2012	43	46	30
2013	46	41	32
2014	46	41	32

Table 1 Classification of firms according to Z-SCORE ALTMAN
Source: Own elaboration

An average of 27% of companies could not be classified according to the Z-score due to lack of accounting data. However, of the remaining 73% of companies in the sample that have been classified, 51% are healthy and 49% are bankrupt. This concludes that we start from a balanced sample of healthy and bankrupt companies for each of the years within the time series analyzed.

On the other hand, the selection of the independent or explanatory variables that will be used in any model is of special importance and attention on the part of the researchers, since based on them it will be possible to draw appropriate and accurate conclusions.

In order to determine the role of macroeconomic variables in the explanation and prediction of business failure, this research paper considered two types of explanatory variables: microeconomic variables (financial ratios) and macroeconomic variables.

For Brealey and Myers (1999), using financial ratios has the advantage of not being overwhelmed by the large volume of information and data contained in financial statements. According to Segovia-Vargas and Camacho-Miñano (2018), an advantage of using ratios is that they reduce the dispersion in the figures of the financial statements of companies due to their size. This fact facilitates the inter-company comparison. Large firms produce large accounting numbers and small firms produce smaller accounting numbers. Therefore, the use of ratios has the advantage of reducing the bias that could arise from the size of firms.

As far as the selection of financial ratios is concerned, this study was carried out taking into consideration the following elements:

1. The data extracted from the financial statements available for the study.

2. The bibliographical review of a considerable number of articles in this line of research. This review took into account the number of papers in which financial ratios were most frequently used (see section 2, Tascón Fernández and Castaño Gutierrez, 2012).

Variable	Definition	Nº Papers	Indicator
X_1	Current Assets/Current Liabilities	1	Liquidity
X_2	Total Liabilities/ Total Assets	18	Indebtedness
X_3	Total Liabilities / Stockholders' equity	3	Indebtedness
X_4	EBIT / Revenues	1	Profitability
X_5	EBIT / Stockholders' equity	5	Profitability
X_6	Net Income / Net revenues	2	Profitability
X_7	Net Income / Stockholders' equity	6	Profitability
X_8	Net Income / Total Assets	14	Profitability
X_9	Revenues / Fixed Assets	5	Efficiency

Table 2 Microeconomic variables (financial ratios)
Source: Own elaboration

The rest of the explanatory variables are the most relevant macroeconomic variables (Hernández-Tinoco and Wilson, 2013) of each of the countries under study (Table 3):

Variable	Definition
Sector	Industry: Classification according to the specialization of the economic activity
País	Country
GII	Global Insolvency Index (Euler Hermes)
TEA	Business Entrepreneurship Index. Early - Stage Entrepreneurial Activity
PIB	GDP- Gross Domestic Product
Desempleo	Unemployment (Rate of unemployment)
Corrupción	Corruption Perception Index
Cumplimento ley	Enforcement: law enforcement index
Inflación	Inflation
Situación legal	Legal situation: Classification according to civil law or common law

Table 3 Macroeconomic variables
Source: Own elaboration

The main characteristics of our sample are shown in the following tables 4 and 5:

Variables	Minimum	Maximum	Mean	Standard Deviation
X_1	0.06	7.63	0.72	0.77
X_2	0.06	0.99	0.66	0.21
X_3	0.06	98.16	5.33	9.72
X_4	-80.90	0.80	-0.18	5.18
X_5	-9.10	1.84	0.05	0.62
X_6	-34.14	1.09	-0.05	2.03
X_7	-3.84	0.88	0.02	0.29
X_8	-0.12	0.11	0.01	0.02
X_9	0.03	209.94	3.13	12.46

Table 4 Descriptive statistics of the selected microeconomic variables
Source: Own elaboration

Variables	Minimum	Maximum	Mean	Standard Deviation
GII	-0.30	0.33	0.03	0.15
TEA	0.00	0.19	0.07	0.05
PIB	-0.03	0.05	0.01	0.02
Desempleo	0.05	0.26	0.12	0.08
Corrupción	0.03	0.09	0.06	0.02
Enforcement	0.42	0.86	0.67	0.08
Inflación	-0.01	0.05	0.02	0.01

Table 5 Descriptive statistics of the selected macroeconomic variables
Source: Own elaboration

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4. Methodologies

We will use two types of methodologies, one parametric and the other non-parametric. The parametric method is based on the analysis of panel data, that is, repeated measurements over a period of time on the same individual, thus obtaining a history that shows the development or evolution of the characteristics being measured. For the application of this methodology, it is necessary an efficient analysis of the databases since when data are missing (they should be estimated) or the presence of atypical data can have a negative or illogical influence on the results. In addition, this efficient analysis can contribute to a better prediction and, therefore, to a better evaluation of the companies under study.

When panel data are available, the use of linear models ignores possible correlations between variables and therefore erroneous conclusions would be reached regarding statistical significance. A tool that is appropriate for analyzing dichotomous variables with this type of data is through generalized estimating equation (GEE), introduced by Liang and Zeger (1986) which are an extension of generalized linear models (GLM), in which the existing correlation between variables is taken into account to increase the efficiency of the estimator.

To estimate β, the GEE is $\sum_{i=1}^{n} \frac{\partial \mu_i^{\tau}}{\partial \beta} V_i^{-1}(Y_i - \mu_i(\beta)) = 0$, where $V_i = \gamma\, A_i^{1/2} R_i(\alpha) A_i^{1/2}$ and being, $R_i(\alpha)$ the correlation matrix. The element *(j, k)* of this matrix is the correlation between y_{ij} and y_{ik}.

The correlation between repeated measures, however, can have an important effect on the estimated variance of the regression coefficients and will, therefore, have to be taken into account to make correct inferences. Since it is rare that the true correlation is known, it is considered a working correlation matrix, R. This matrix is of size t x t because it is assumed that there is a fixed number of points in time at which individuals are observed. In addition, the correlation matrix R_i is considered to depend on a vector of association parameters, denoted by α. This unknown vector of parameters has a structure that will be determined by the researcher.

There is not much information on how to choose the best correlation structure and it is often difficult to determine. However, the possible loss of efficiency is reduced as the number of individuals grows. Unstructured was used in this paper. In addition, GEEs perform better when the following conditions are met:

- The number of observations per subject is small (5 observations per company in this study) and the number of subjects is large (119 companies in this study).

- These are longitudinal studies or, to put it another way, with a panel data structure, always obtaining measurements at the same instant of time for each individual (2010 - 2014 in the present study).

When using the GEE model, it should be noted that it is a model that is not based on the use of the likelihood function. One of the criteria most used and implemented in different data analysis packages is Wald's statistic. This criterion can be used to select the best structure of the R_i matrix (α) according to the data, or to select variables to be taken into account within the model and previously requires a rigorous analysis of the data. Therefore, the first analysis of the predictive model does not have to consist of mainly estimating the predictive model, but of evaluating the underlying assumptions that are as important as the final result.

A second method is a non-parametric approach based on Artificial Intelligence (AI), i.e., it does not start from previously established hypotheses, and considers the baseline data in a fully exploratory manner. The IA is in charge, among other applications, of building computer programs capable of carrying out intelligent work based on learning from the data by means of pattern recognition, with the purpose of extracting information that allows establishing properties and characteristics of a certain set of objects. Of all the artificial intelligence techniques, we have selected the decision trees for their easy comprehension for the end user and for their explanatory power.

Decision trees are part of so-called automatic learning and are diagrams of logical constructions of the optimal classification of a given group of data according to their characteristics or attributes.

According to Molina and García (2006) a decision tree can be interpreted as a series of compacted rules for its representation in the form of a tree and what differentiates one decision tree from another is the algorithm that generates it and that will make the successive partitions in the space of explanatory variables, using in each partition a single variable. There are numerous algorithms to elaborate a decision tree, but one of the most used in the literature is the one developed by Quinlan (1993) and implemented in C4.5 (as an example, see Díaz-Martínez, Segovia-Vargas and Fernández Menéndez, 2005; Gelashvili, Segovia-Vargas and Camacho-Miñano, 2015). This algorithm generates a decision tree from the data using recursive partitions, partitions supported by a series of concepts from information theory (Reza, 1961). The basic idea is to take in each branch of the tree, to make the corresponding partition, that variable that provides more information. It uses a heuristic technique known as a gain ratio which is a measure based on information that considers different numbers and (different probabilities) of the test results. Thus, the algorithm generates a rule structure and evaluates its goodness using criteria that measure the precision in the classification of cases.

Results and discussion

1. Principal component analysis

First, a preliminary analysis of the data was made using the statistical technique known as principal component analysis. The following criteria will be used to select the components:

- Kaiser criterion: This criterion mentions that the eigenvalues have to be greater than 1, since these are the ones that explain greater variance. The average of all these values is equal to 1.

- Choose a minimum of variance that you want to explain. For this study, we set a target between 65% and 75%.

Taking into account these criteria, we have chosen 4 components for each of the years analyzed, observing which variables saturate each factor in each of the years (those that have more weight within each of them).

In the space of the variables, the analysis makes sense if there are positive variabilities of the variables, since this is indicative of their greater incidence on the total absolute variability, and therefore the other factors will have little incidence.

Figure 1 shows the variables that saturate each factor for each of the years and for the 4 main components selected. Figure 2 includes a summary considering the frequency of appearance of these variables:

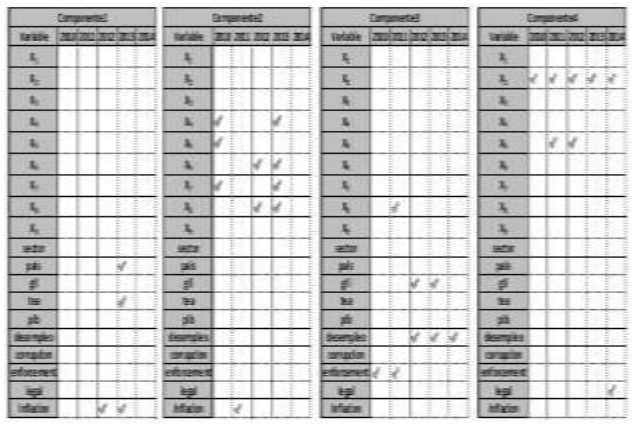

Figure 1 Principal Component Analysis
Source: Own elaboration

Variable	Comp 1	Comp 2	Comp 3	Comp 4	Total
X_1	0	0	0	0	0
X_2	0	0	0	5	5
X_3	0	0	0	0	0
X_4	0	2	0	0	2
X_5	0	1	0	2	3
X_6	0	2	0	0	2
X_7	0	2	0	0	2
X_8	0	2	1	0	3
X_9	0	0	0	0	0
Sector	0	0	0	0	0
Pais	1	0	0	0	1
GII	0	0	2	0	2
TEA	1	0	0	0	1
PIB	0	0	0	0	0
Desempleo	0	0	3	0	3
Corruption	0	0	0	0	0
Enforcement	0	0	2	0	2
Legal	0	0	0	1	1
Inflacion	2	1	0	0	3

Figure 2 Frequency summary of variables by component
Source: Own elaboration

2. Generalized estimating equation model

The analysis of main components gives us an idea of the independent variables that could form part of the model without losing information from the rest of them, and from them, the iterations of the GEE model have been carried out:

Wald X^2= 93.13		
Variable	**p-value (P>│z│)**	**Coeficient**
X_2	0.000	7.114
X_5	0.049	-1.073
X_8	0.000	-30.904

Wald X^2 (6) = 107.83		
Variable	**p-value (P>│z│)**	**Coeficient**
X_1	0.000	-1.932
X_2	0.000	6.742
X_5	0.007	-1.501
X_8	0.000	-33.829
Unemployment	0.007	3.566
Inflaction	0.095	13.185

Wald X^2 (4) = 116.96		
Variable	**p-value (P>│z│)**	**Coeficient**
X_1	0.000	-1.91
X_2	0.000	6.88
X_5	0.019	-1.24
X_8	0.000	-31.39

Figure 3 Iterations of GEE model
Source: Own elaboration

As regards the interpretation of the coefficients in financial terms, it should be pointed out that the main variables explaining business failure in the sample of listed companies used are the following:

- The negative coefficient of variable X_1 (liquidity ratio): Indicates that a company is more likely to go bankrupt when, for each monetary unit of debt, it has fewer liquid assets to meet its obligations.

- The positive coefficient of variable X_2 (global debt-solvency): Indicates that a company is more likely to go bankrupt when it is more dependent on its debt. In other words, for each monetary unit of the total asset, more depends on external resources.

- The negative coefficient of variable X_5 (return on capital): Indicates that a company is more likely to go bankrupt when for each monetary unit of capital invested by shareholders generates less profit before taxes and interest.

- The negative coefficient of variable X_8 (ROA or return on assets): Indicates that a company is more likely to go bankrupt when less operating profit is generated for each monetary unit invested in assets.

After the third iteration, the same variables are maintained as significant within the GEE model, and its predictive capacity was improved by adding variable X_1. Thus, we can conclude that the variables within the third iteration are those that would have greater predictive power in relation to the dependent variable, i.e. the possible bankruptcy of a company. In this way, we demonstrate that macroeconomic variables do not have sufficient weight in the prediction of possible insolvency in listed companies as the sample used.

3. Decision Tree Model

As a robustness analysis, we are going to contrast the results obtained previously with the decision tree methodology. Although the data we have presents the characteristic of panel data, for the application of these models only two cross sections will be made, one for 2010 and another for 2014, so we can analyze the beginning and end of the time series.

The obtained results[2] of the C4.5 decision tree for 2010 are shown in the following figure (figure 4):

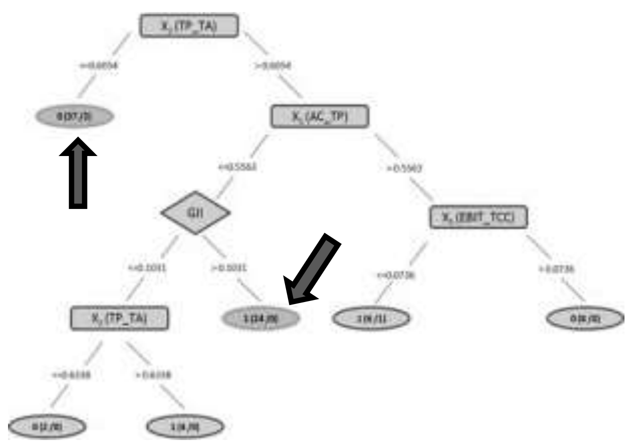

Figure 4 C4.5 Decision Tree year 2010
Source: Own elaboration. Note: The arrows point to the strongest branches.

The 10 k-fold cross validation result (which the most common)[3] of this model is 77% of correct classifications.

[2] WEKA is the data mining package developed by the University of Waikato (Witten and Frank, 2005) with which we performed our analysis.

[3] In cross validation, a random partition (usually 10 parts) of the development group (the entire sample data) is performed and a subgroup (9 parts) is used recursively to generate the tree and another (1 part) for validation.

The branches that verify more companies (stronger) are those that we must analyze and interpret since they would reflect certain patterns since they are supported by the majority of the cases. To analyze bankruptcy (class 1) we have the following branches that represent the strongest rule:

- Branch 1. All companies, according to the classification criteria provided by the response variable (bankruptcy or no bankruptcy), can be classified according to first to the microeconomic variable known as the global solvency ratio X_2. The higher the result of this quotient, the more the company depends on outside resources. For values higher than 0.6054 in this ratio, the tree suggests the analysis of another additional variable, i.e. the microeconomic variable X_1.

- Branch 2. This branch corresponds to the analysis of variable X_1, the financial ratio of current liquidity that measures the share of total financing in short-term investments, the greater the ratio, the greater the short-term liquidity of the company. The decision tree suggests the analysis of the Macroeconomic variable GII for values lower than 0.5563.

- Branch 3 refers to the analysis of the variable GII (global insolvency index). The higher this indicator, the lower the level of solvency of a company. For values greater than 0.1031 the company would be classified as bankruptcy, a situation that is fulfilled in 24 cases, i.e. a total of 30% of the sample.

In the same way, we will analyze the healthy companies (class 0- no bankruptcy) we have the following branches that represent the strongest rule. In this case, we have a single branch that, following the same criterion, shows that all companies can be classified by first taking into account variable X2.

Analyzed inversely, the lower the result of this quotient, the less the company depends on external resources. That is why the tree suggests that for values lower than 0.6054 of this variable, the company would be classified directly as healthy without the need for any other additional variable, a situation that is fulfilled in 37 cases, that is, a total of 46% of the sample.

The results obtained after the application of a tree C4.5 for the year 2014 are shown in the following figure 5:

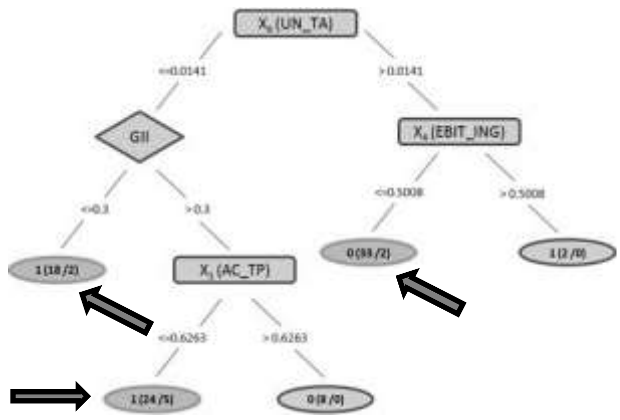

Figure 5 C4.5 Decision Tree year 2014
Source: Own elaboration. Note: The arrows point to the strongest branches

The 10 k-fold cross validation result of this model is 71.76% of correct classifications. In the same way, we will analyze and interpret the branches that present greater force.

To analyze bankruptcy (class 1) we have two rules. The first rule for bankrupt enterprises contains two branches:

- Branch 1. All companies, according to the classification criteria provided by the response variable (bankruptcy or no bankruptcy), can be classified according to microeconomic variable X_8, profitability ratio known as ROA (return on assets). A low ratio is associated with low productivity or the inefficiency of its assets. For values lower than 0.0141 in this ratio, the tree suggests the analysis of another additional variable, i.e. the macroeconomic variable GII.

- Branch 2. Corresponds to the analysis of the variable GII, (global insolvency index). For values lower than 0.3, the company would be classified as bankruptcy, a situation that occurs in 18 cases, i.e. in a total of 21% of the sample.

The second rule for bankrupt enterprises contains three branches:

- Branch 1. All enterprises can be classified by first looking at the microeconomic variable X8 known as the economic profitability ratio or ROA.

For values lower than 0.0141 in this ratio, the tree suggests the analysis of another additional variable, i.e. the macroeconomic variable GII.

- Branch 2. It corresponds to the analysis of the macroeconomic variable GII (global insolvency index, the higher this indicator, the lower the level of solvency of a company). For values greater than 0.3 in this indicator, the tree suggests the analysis of another additional variable, i.e. microeconomic variable X_1.

- Branch 3. It corresponds to the analysis of variable X_1, (current liquidity coefficient). For values lower than 0.6263 in this variable, the company would be classified as bankruptcy, a situation that is fulfilled in 24 cases, i.e. a total of 28% of the sample.

Similarly, we will analyze healthy enterprises (class 0-no bankruptcy) for which we only have one strong rule with two branches:

- Branch 1. All enterprises can be classified first by the microeconomic variable X_8, i.e. by the ROA. As mentioned above, a high ratio is synonymous with very efficient and productive assets. For values greater than 0.0141, the tree suggests the analysis of another additional variable, i.e. microeconomic variable X_4.

- It corresponds to the analysis of the microeconomic variable X_4 or net profit margin or profitability of income; it indicates how much profit is obtained by each monetary unit of sales and therefore, the lower the indicator, the less profit is obtained by the sales made. For values lower than 0.5008, the company would be classified as bankrupt, a situation that is fulfilled in 33 cases, i.e. a total of 39% of the sample.

From the analyses carried out, it can be inferred that in order to identify the micro and macroeconomic variables that are most significant for analyzing the probabilities of early business failure, the ratios X_1 (current liquidity coefficient), X_2 (global solvency ratio) and X_8 (ROA) are the variables to be taken into account and with the patterns shown by the rules.

4. Results and discussion

The results show that increasing the predictive capacity or power of business failure prediction models can be approached from two different approaches. The first of these approaches relate to the appropriate choice of variables and the second relates to the appropriate choice of methodology or application technique used. In general terms, the research work carried out in this sense indicates that the precision of bankruptcy models cannot be appreciably improved by the choice of one or another classification algorithm. For example, in the work carried out by Karas and Režňáková, (2014) for the case of companies in the Czech Republic, a parametric vs. a nonparametric method applied to the same initial sample was tested and obtaining as results for the case of the parametric methodology (discriminant analysis) 8 significant ratios and 7 for the case of the nonparametric (trees), obtaining 3 ratios in common. At the same time, Olmeda and Fernández (1997) compare the precision of parametric and non-parametric classifiers suggesting that an optimal system for risk classification should combine two or more different techniques.

The results presented in this research work show that the application of parametric and nonparametric techniques does not show significant differences for the variables with the best predictive capacity. As can be seen in Table 6, under these two approaches, the microeconomic variables or financial ratios that present greater predictive power X_1, X_2, X_8 are coincident. Variable X_2 (overall solvency ratio) and variable X_8 (return on assets - ROA) have been present in most of the research work related to business failure.

It is to be expected that these variables will have great relevance in the study since, on the one hand, the global solvency ratio relates the totality of assets that a company has to meet its total obligations, the same relationship that indicates that the more dependent the company is on external resources, the greater the possibility of filing for bankruptcy.

On the other hand, the ROA or profitability on assets shows how much cash the company's assets are being and, therefore, they generate greater profitability, causing at the same time that the company has the capacity to solve the financing that the company has from external resources.

The X_1 ratio (current liquidity ratio) is part of the liquidity factors and its presence as a significant ratio within the models is more than justified because these indicators demonstrate the overall ability of a company to pay its debts (short and long term), if necessary by liquidating the assets quickly or converting them into cash.

Method/variable	Microeconomics (financial ratios)					Macroeconomics
	X_1	X_2	X_4	X_5	X_8	GII
EEG (parametrics) 2010-2014	✓	✓		✓	✓	
Decision trees (non-parametrics) 2010	✓	✓			✓	✓
Decision trees (non-parametrics) 2014	✓		✓		✓	✓

Table 6 Coincidence of Micro and Macroeconomic variables in the analysis
Source: Own elaboration

The results obtained by applying both techniques (Table 6) show that macroeconomic variables do not have the same presence as financial variables.

This may be largely due to the fact that the diverse macroeconomic conditions presented by each of the countries may pose problems of comparability of information and, therefore, place greater weight on internal variables. In other words, macroeconomic variables are diluted in an environment of listed companies.

Therefore, the hypothesis put forward is not accepted, demonstrating that in a context of listed companies, macroeconomic variables would not condition business failure.

Conclusions

The aim of this study is to analyze the role that macroeconomic variables can play in predicting business failure. The results obtained in the empirical application of the two techniques used allow us to conclude that the most significant ratios in terms of predicting business failure or bankruptcy are the short-term liquidity ratio (X_1), the solvency ratio (X_2) and economic profitability (X_8), which in turn are associated with factors of liquidity, indebtedness, and profitability, respectively.

The methodologies used, GEE and decision trees, offer the opportunity to use longitudinal designs for response variables that do not necessarily have a normal distribution.

The present research work presents as a novelty with respect to other empirical studies the application of a model that allows working with panel data that considers the specification of the form of correlation of the variables as well as the inclusion of macroeconomic variables, whose results have been contrasted with the artificial intelligence methodology known as decision trees. In our case, given the difficulties indicated and the type of sample we had in which companies from different countries participated and therefore the legal classification criteria vary within each country, we opted for the application of the economic approach, establishing as its definition to classify failed companies the score obtained through the application of the model known as Altman's Z-score.

This paper presents some limitations. Although we worked with all the companies for which financial statements were available for the period 2010 - 2014, thus increasing the size of the sample, due to the limitations of the information, there were accounting items for which data were not available and therefore it was not possible to estimate the ratio for that particular period; however, this limitation in the estimation of the model is attenuated through the consideration of several periods for each company.

However, we consider that all financial models for the prediction of business failure should only be taken as a reference parameter, that is, only as an indicator and as a support tool for the business diagnosis, and should be complemented with the different types of corresponding financial analysis as well as with the experience observed through the years and the socioeconomic environment in which the company under study performs.

There is no doubt that in the last few decades the analysis of business solvency has become a key piece and an issue of concern worldwide, mainly due to the increase in the number of business bankruptcies (which are more frequent day by day regardless of geographical location or developed economic activity), the development of new financial instruments and, in general, to the globalization that has great importance for companies since it allows free trade and opens up competition in international markets.

With what has been said so far and after having tackled the problem of a business bankruptcy or failure from two different perspectives, we can conclude that there are great survival challenges that companies face worldwide and that would be the object of future lines of research.

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December 2019 Vol.10 No.23 1-18

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