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EFFECTIVENESS OF THE BUSINESS FAILURE PREDICTION MODELS IN THE IBERIAN TRANSPORT COMPANIES

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ABSTRACT

Purpose: validate, in the existing models, its effectiveness and ability to provide useful information for decision-making, allowing the choice of one that presented as the best alternative for predicting bankruptcy for companies in the transport economic sector (NACE H) up to 6 years before it occurs.

Theoretical Framework: in the last decades, since Beaver's (1966) preliminary work in bankruptcy prediction, followed by Altman (1968) models, numerous authors developed different techniques and models to this purpose. Of all the techniques used and developed in almost 60 years of bankruptcy prediction study, Multivariate Discriminant Analysis (MDA) stands out. Despite its limitations, it best combines management and usage simplicity offering stable levels of efficiency.

Design/Methodology/Approach: we selected, Portuguese and Spanish companies, from the transport and storage economic sector, subject to statutory auditing, in a sample of 22 companies, considered healthy, according to the most common criterion in the literature: Equity above zero, during six and that in the seventh were considered bankrupt (Equity below zero) and another, paired with the previous one, by Total Assets and Revenues, with 36 companies that presented Equity above zero throughout all the analyzed period, granting the analyzed models full forecasting potential. Were used 21 multi-sectorial models, for different timelines and geographies, with a greater presence in the literature, or developed by Edward Altman, a unique researcher on this subject, between 1979 and 2014.

Findings: As a main conclusion, in addition to the description of models and techniques, the formulations developed by Carvalho das Neves (1998), Lizarraga (1998) and Monelos et al. (2011) were the best predictors of bankruptcy, up to 6 years before it occurs, for Portuguese and Spanish companies in the transport economic sector (NACE H).

Research, Practical & Social Implications: This information can be used by any interested entity to improve current conditions, optimize and enhance the usage the bankruptcy forecast models.

Originality/Value: The global financial crisis and the growing number of company closures make it crucial to understand the causes of corporate failure, with emphasis on forecasting and anticipating it.

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EFICÁCIA DOS MODELOS DE PREVISÃO DE FALÊNCIA EMPRESARIAL NAS EMPRESAS IBÉRICAS DE TRANSPORTES

RESUMO

Objetivo: validar, nos modelos existentes, a eficácia para disponibilizar informação útil para a tomada de decisão, permitindo a escolha do que seja a melhor alternativa para a previsão de falência nas empresas do sector dos transportes (CAE Rev 3 – H) até 6 anos antes.

Referencial Teórico: nas últimas décadas, desde os trabalhos preliminares de Beaver (1966) na previsão de falência, seguido pelos modelos de Altman (1968), numerosos autores desenvolveram diferentes técnicas e modelos para esse fim. De todas as técnicas utilizadas e desenvolvidas em quase 60 anos de estudo da previsão de falência, destaca-se a Análise Discriminante Multivariada (MDA). Apesar das suas limitações, esta é a que combina melhor a gestão e simplicidade de utilização, oferecendo níveis estáveis de eficiência.

Desenho/Metodologia/Abordagem: selecionamos, empresas portuguesas e espanholas, do sector dos transportes e armazenagem, sujeitas a revisão legal de contas, numa amostra com 22 empresas consideradas saudáveis, segundo o critério mais comum na literatura: Capitais Próprios superiores a zero, durante seis anos e que no sétimo foram consideradas falidas (Capitais Próprios inferiores a zero) e outra, emparelhada com a anterior, pelo Total de Balanço e Reditos, com 36 empresas que apresentaram em todo o período analisado Capitais Próprios superiores a zero, concedendo aos modelos em análise uma potencialidade plena de previsão. Às amostras foram aplicadas 21 formulações multissectoriais, desenvolvidas entre 1979 e 2014, para diversos horizontes temporais e geografias, com maior presença na literatura, ou por Edward Altman, investigador ímpar nesta temática.

Resultados: como principal conclusão, alem da descrição dos modelos, identifica-se que as formulações desenvolvidas por Carvalho das Neves (1998), Lizarraga (1998) e Monelos et al. (2011) constituem os melhores previsores de falência, até 6 anos antes de esta ocorrer, para as empresas ibéricas, que laborem no sector dos transportes e armazenagem (CAE H).

Pesquisa, Implicações Práticas e Sociais: estas informações podem ser utilizadas pelas entidades interessadas para melhorar as condições atuais, otimizar e potenciar a utilização dos modelos de previsão de falência empresarial.

Originalidade/Valor: A crise financeira global e o crescimento do número de encerramentos de empresas, torna crucial compreender as causas da falência, com particular ênfase na sua previsão e antecipação.

Palavras-chave: Análise Discriminante Multivariada, Falência Empresarial, Modelos de Previsão.

EFECTIVIDAD DE LOS MODELOS DE PREVISIÓN DE FRACASO EMPRESARIAL EN LAS EMPRESAS DE TRANSPORTE IBÉRICO

RESUMEN

Objetivo: Validar en los modelos existentes la efectividad de proporcionar información útil para la toma de decisiones, permitiendo la elección de cuál es la mejor alternativa para predecir la quiebra en las empresas de transporte (PPA Rev 3 - H) hasta 6 años antes.

Referencia Teórica: en las últimas décadas, desde el trabajo preliminar de Beaver (1966) sobre previsión de quiebra, seguido de los modelos de Altman (1968), numerosos autores han desarrollado diferentes técnicas y modelos para este fin. De todas las técnicas utilizadas y desarrolladas en casi 60 años de estudio del pronóstico de quiebra, se puede destacar el Análisis Discriminante Multivariado (MDA). A pesar de sus limitaciones, este es el que mejor combina la gestión y la sencillez de uso, ofreciendo niveles estables de eficiência.

Diseño/Metodología/Enfoque: Seleccionamos empresas portuguesas y españolas, del sector del transporte y almacenamiento, sujetas a auditoría legal, en una muestra con 22 empresas consideradas saneadas, según el criterio más común en la literatura: Capital propio superior a cero, durante seis años y que en el séptimo fueron consideradas en quiebra (Capital inferior a cero) y otra, emparejada con la anterior, por Total Balance e Ingresos, con 36 empresas que presentaron durante todo el periodo analizado Capital propio superior a cero, otorgando los modelos bajo análisis pleno potencial de previsión. Las muestras fueron aplicadas a 21 formulaciones multisectoriales, desarrolladas entre 1979 y 2014, para diferentes horizontes temporales y geografías, con mayor presencia en la literatura, o por Edward Altman, investigador único en este tema.

Resultados: como principal conclusión, además de la descripción de los modelos, se identifica que las formulaciones desarrolladas por Carvalho das Neves (1998), Lizarraga (1998) y Monelos et al. (2011) son los mejores predictores de quiebra, hasta 6 años antes de que se produzca, para las empresas ibéricas que trabajan en el sector del transporte y almacenamiento (CAE H).

Investigación, Implicaciones Prácticas y Sociales: esta información puede ser utilizada por las entidades interesadas para mejorar las condiciones actuales, optimizar y aprovechar el uso de modelos de previsión de quiebras empresariales.

Originalidad/Valor: La crisis financiera mundial y el crecimiento del número de cierres de empresas hacen que sea crucial entender las causas de la quiebra, con especial énfasis en la previsión y la anticipación.

Palabras clave: Análisis Discriminante Multivariado, Quiebra Corporativa, Modelos de Previsión.

INTRODUCTION

In recent years, the financial world has become very different from what it had been since the recovery from the Great Depression of 1929.

In 2007, a financial crisis caused the world economy to hit rock bottom once again. The origin of this crisis, the subprime crisis, was the willingness of financial institutions to approve low-quality credits, such as NINJA loans, which caused a prolonged and deep economic contraction, affecting all sectors of activity and countries.

The Greek public debt crisis, the bailouts of other European countries and the liquidity support provided to banks and other financial institutions around the world highlighted the need to anticipate and predict these situations so that contingency measures could be taken timely, or, if not, at least to make it possible to mitigate the adverse effects.

In the last decades, since Beaver's (1966) preliminary work on applying univariate analysis to bankruptcy prediction, followed by Altman (1968) and his Multivariate Discriminant Analysis (MDA) models, after them, numerous authors had developed different techniques and models for this purpose.

Of all the techniques used and developed in almost 60 years of studying and predicting bankruptcy, MDA stands out. Despite its limitations, no other modeling technic has been identified that combines its management, interpretation and application simplicity and that offer similar levels of classification efficiency.

MAIN APPROACHES AND TYPES OF MODELS: CHARACTERISTICS AND LIMITATIONS

Several authors indicate that the first studies on the prediction of corporate bankruptcy emerged in the USA in the 1930s, after the Great Depression. However, according to Divsalar et al. (2011), interest in the subject only gained real momentum in the 1960s with the application of statistical techniques.

There are numerous studies on bankruptcy and its prediction. In response, Aziz and Dar (2004), Bellovary et al. (2007), Pereira et al. (2010), Fernández and Gutiérrez (2012), Jackson and Wood (2013), Sun et al. (2014), Peres (2014) and Peres and Antão (2017) suggest the following grouping for techniques applied to predicting corporate bankruptcy:

Statistical approach

Historically, this was the first model type to emerge, usually being simple, easy and quick to use.

Although research on this subject began in the 1930s, the first univariate analysis model appeared with Beaver's study in 1966, which used a set of indicators applied successively and separately to classify if a company is healthy or not.

However, this approach had some inherent limitations. Altman (1968, p.591) gave an example of this issue, stating that "a company with a poor record of profitability and / or solvency may be regarded as potentially bankrupt. However, because of its above-average liquidity, the situation may not be considered serious."

Natural evolution has led to the expansion of the univariate analysis by keep on considering several indicators but making it simultaneously. According to Bellovary et al. (2007, p.4), Beaver, in his suggestions for future research "indicated the possibility that multiple ratios considered simultaneously might have greater predictive capacity than single ratios - and thus began the evolution of bankruptcy prediction models."

Thus, in 1968 Altman combined several indicators into a discriminant function, demonstrating a strong improvement in the forecasting ability, thus creating the named Z-Score model, and with it, the application of MDA to the bankruptcy prediction, demonstrating a marked improvement in forecasting accuracy.

This approach includes not only analyses as univariate and MDA, but also logit, probit and cumulative sum control charts, among others.

Artificial Intelligence Expert Systems (AIES)

The availability of computers and the technological advances, especially since the 1980s, led to the creation of more technology-orientated models. AIES emerged as an alternative to the classic statistical approach models that had been in use for a long time. Computers can simulate human cognitive intelligence as well as problem-solving behavior. This discovery led to a search for programs that could adequately simulate these human abilities, giving rise, in the 1950s, to the field of research that became known as Artificial Intelligence.

This approach includes technics as neural networks, support vector machines, case-based reasoning, rough sets and decision trees, among others.

Theoretical Approach

This is one of the approaches that has emerged more recently, based on a critique of the focus of the statistical and AIES models. According to critics, since the models using those technics are built without any theoretical basis, they will focus on the corporate bankruptcy symptoms rather than the causes. Predicting bankruptcy without adequate theoretical support has long been questioned, leading researchers to attempt to support their explanations of the bankruptcy process theoretically.

Some examples of models within the theoretical approach are gambler's ruin, balance sheet decomposition measure and cash management, among others.

DISCRIMINANT ANALYSIS

As a statistical method, it detects the attributes of the elements of one group that might distinguish them from those of the other. Based on these different characteristics, it is then possible to predict to which group a new element will likely belong to.

Once formulated and applied, this method will essentially tell us whether the characteristics of the company being analyzed are more similar to the ones belonging to group A (bankrupt) or B (non-bankrupt).

From a technical point of view, it is assumed that the data used follows a normal multivariate distribution, although violating this assumption doesn’t usually have serious implications. In addition, it is also assumed that the variance / covariance matrices between the groups are homogeneous. However, small deviations aren’t particularly important, so in many cases, the analysis remains valid even without the strict fulfilment of the assumptions.

Since this is the most extensively studied technique, it is also easier to identify its sensitivities or limitations.

- Territorial Sensitivity: a model designed for a particular geography will potentially perform differently when applied to a sample from a different location. Countries may differ in legal requirements, accounting, tax and labor systems, characteristics of their financial systems and, ultimately, macro and microeconomic policies, cultural issues and traditions that might affect the management style;

- Activity Sector sensitivity: each economic sector has its specific characteristics, from the performance of its financial indicators to the intrinsic details of its operation, and there are financial indicators that behave in a specific way depending on the sector;
- Temporal sensitivity: it is unlikely that a model designed in the middle of the 20th century will have the same classification performance when applied to a sample of current companies, even if they are from the same country and activity sector, have the same size and characteristics as the ones used to design the model in the first place;
- Sensitivity to bias in sample selection: non-random sampling, without any specific treatment or selecting the entire population, results in the inclusion of more cases of one type than the other (healthy or bankrupt) in the model-building phase, which could naturally make it biased later when it comes to classifying companies as similar to the group A or B;
- Sensitivity to selection assumptions: in addition to all the previous sensitivities, the model is also defined by the analyst's opinion on which indicators should or not be included, as well as the tests to be carried out, the sub samplings to be made and any other measures to be implemented to deal with the problems that arise.

ECONOMIC AND FINANCIAL ANALYSIS AND READING INDICATORS

The characteristics that can be deduced from the indicators containing the company's accounting information include its financial health, performance and its perception by stakeholders.

According to Brealey and Myers (2010) and Ross et al. (2002), financial analysis is generally seen as a key to unlock what is hidden in the accounting information, but it isn’t a crystal ball, it is simply the summary of financial information that helps analysts ask the right questions by facilitating comparisons between years and companies.

We can take a narrow view of the financial analysis and see only the relationship between Balance Sheet items or between the level of execution from one year to the next, or we can see it as Breia et al. (2014) do, interpreting it more broadly as a tool that offers two perspectives: internal and external. The first refers to the requirements of the company's finance department and the last to the entities that, in one way or another, deal with the company (suppliers, banks, creditors in general, customers, investors, etc.).

Over time, accounting standards have been defined and redefined to help create a stricter regulatory environment. However, companies still have some freedom to decide how to communicate their results (closer or not to the tax criteria, with a, more or less, effective validation of its continuity assumptions, etc.) and what to show or not on the Balance Sheet. That said, effective financial analysis requires the analyst to go beyond appearances and attempt to understand some of the decisions made by those responsible for the company's accounting.

ANALYZED MODELS

In line with Peres and Antão (2017, p. 118-120), we sought to explore the most common characteristics of the MDA approach models, with a multi-sector sample, developed by Portuguese and Spanish authors or by Edward Altman, a unique researcher in corporate bankruptcy prediction. We identified 21 different formulations in the period 1979-2014.

Table 1 summarizes the identified studies by the countries of the samples used by their respective authors.

Table 1. Researched Models by country

Brazil	2
Canada	1
Spain	14
Portugal	2
USA	2
	21

Source: Own Elaboration

We have searched for the multi-sectoral models considered most relevant in the literature from the countries in the samples we will use, Portugal and Spain, to which we have added those, with the same characteristics, developed more recently by Edward Altman totalizing 21.

Table 2. Number of models, per type of data processing method used in the sample

Matched	2
Paired	14
No treatment	5
	21

Source: Own Elaboration

Focusing on the type of data processing method used on the model's sample, table 2 shows that around 23,8% of the authors didn't do any treatment to it and that the most common alternative is the paired sample, which advocates that for each company considered bankrupt, only one other company of similar size and characteristics will be matched in the healthy sample. In contrast, in the matched samples there will be one or more companies in the healthy.

Table 3 shows that the models cover an average period of eight years of financial data. And as for the distribution of the samples between bankrupt and non-bankrupt companies, the first ones wight around 57,7% of the total companies analyzed.

Table 3. Main characteristics of the collected models

			Sample		Accrued Classification		Error	
	# Years	# Ratios	# F	# NF	%F	%NF	Type I	Type II
Average	8	4	79	58	83,5%	78,8%	16,5%	21,2%
Standard Deviation	4,9	1,5	77,5	26,3	7,9%	23,4%	7,9%	23,4%

Source: Own Elaboration

It can also be observed that the studies use an average of 4 indicators, obtaining an overall average correct classifications rate around 81,2%, with an average error rate of 19,8%.

FINANCIAL ANALYSIS AND THE MODELS' INDICATORS AND RATIOS

Many characteristics can be deduced from the ratios containing the company's accounting information, such as its financial health, performance and competitive trends.

The 21 identified models have a wide variety of economic and financial ratios. Each model combines between 2 and 8 of them to predict the financial state of the company being analyzed. These models overall use 26 different ratios, present in Appendix I.

In general terms, their ratios can be divided into the following main groups:

1. Capital Structure: essentially oriented towards the long term, show us how overloaded with debt the company is, i.e. the degree to which it uses borrowed capital; this group has 6 ratios;
2. Liquidity: assess the ability to meet short-term commitments in a general sense; the higher they are, the greater the company's ability to meet them. They have some characteristics that may be ambiguous for the information user, such as the Current Assets and Liabilities (short term) being easily changed, so liquidity measures are easily out of date. This group has 5 ratios;
3. Profitability: in a generic sense, they correspond to the relation between the results obtained and the resources used, specifically expressing the relation in terms of magnitude between any given result and the Sales or Invested Capital. These ratios are

useful as a complementary analysis rather than as effective sources of information on their own. These include 7 ratios;

4. Operation or efficiency: these seek to characterize aspects of the activity, such as fiscal and financial efficiency or in the use of resources or assets, etc.; 3 indicators belong to this group;

5. Relative weight ratios: corresponding to the weight of a given item in the the balance sheet subgroup total to which it belongs; this group includes 3 ratios.

6. Dummies and dichotomous: use machine or binary language taking the value 0 or 1 depending on whether the entity meets the criterion they refer to; this group has 2 ratios.

After analyzing all the ratios, and in particular, the groups to which they belong, it can be concluded that in the 21 analyzed models, most of their ratios (90) belong mainly to the groups capital structure (32), profitability (25) and operation or efficiency (15), highlighting the authors' search for a relationship of dependence between corporate bankruptcy and the worsening of the indicators belonging to each of these groups. However, it should also be emphasized that, as Carvalho (2013) points out, a prediction of bankruptcy doesn't necessarily mean that it will happen. It should also be noted that the relative weight and dichotomous groups (with 3 and 2 indicators, respectively) have a fewer number than the previous ones, essentially because they can vary greatly depending on the company's sector of activity or type of business.

Table 4 shows the number of times each of the different indicators appeared in the models analyzed, with those similar, equivalent or complementary been converted.

Table 4. Repetition of Indicators Observed in the Models under Study

# Occurrences	# Ratios
1	8
2	2
3	8
4	1
5	1
6	2
7	2
9	1
10	1
	26

Source: Own Elaboration

There is thus a slight predominance of the ratios present in 14% or less of the different models under analysis (1 to 3 occurrences, 18 indicators), representing 69,2% of the different ratios identified. The remaining 30,8% relate to indicators with between 4 and 10 occurrences, which are present in 19,0 to 47,6% of the 21 models under study, summarized in 8 indicators, listed in Appendix I, specifically those with numbers 9 to 13, 15, 16 and 19, belonging to the capital structure, liquidity, profitability and efficiency groups described in topic 4.1, with a clear predominance of the first of these.

METHODOLOGY

The methodology used involved a series of phases intending to identify the most effective bankruptcy forecasting model to the transport and storage sector in Portugal and Spain.

In terms of methodology, the following phases were followed:

1. Pre-qualification of the bankruptcy prediction models to be involved in selecting the most suitable one for the objectives set.
2. Companies selection:
    a) Portuguese and Spanish;
    b) that carry out their main activity in NACE H - Transport and storage;
    c) subject to a Statutory Audit, following Article 262 of the Portuguese Companies Code and Article 263 of Royal Legislative Decree 1/2010 of 2 July;
3. Validation of the classification of the companies to be included in the sample as bankrupt: that in the last of the seven years of the collected financial data fulfil the selected bankruptcy criterion (equity below zero, as indicated by Peres and Antão (2017), OTOC (2011) and Aziz and Dar (2006)) and cumulatively don’t fulfil it in the first six years.
4. Validation of the classification of companies to be included in the non-bankrupt sample: that trough all the seven years of data do not, cumulatively, fulfil the bankruptcy criterion for this dissertation (equity below zero, as indicated by Peres and Antão (2017), OTOC (2011) and Aziz and Dar (2006)) in a sample paired by size with those methodology’s topic 3.
5. Application of the models under study - to collect the classification of each one - to the companies in the samples indicated in points 3 and 4 of the methodology.
6. Assess which model(s) have the highest-level of accuracy and / or the lowest error in classifying companies as bankrupt or not and compared it with their disclosed accuracy levels.

THE SAMPLE AND DATA PROCESSING

After applying the segmentation criteria set out in subsections 3 and 4 of the methodology to Bureau Van Dijk's AMADEUS databases, we obtained a total paired sample of 58 companies, 22 of which fall into the sub-sample of bankrupt companies (subsection 3) and the remaining 36 into the sub-sample of non-bankrupt companies (subsection 4). The samples, with the companies, their nationalities and tax identifications are in Appendix II and III.

The financial information contained in the Balance Sheet and Income Statement for seven subsequent years, as well as the number of employees, were collected from the database.

All this information was compiled, together with the formulation of the ratios used to formulate the 21 models under study identified in topic 5, which are specific combinations of 26 different indicators, and a matrix was then drawn up for each company providing each model's classification, cross-referencing each of these with the seven years under analysis.

Although the year 2016 was also calculated, analyzed and classified, it won't be taken into account when selecting the most effective model, since it is through that year that each company is pre-classified as bankrupt or not bankrupt, as indicated in Methodology's topic 3.

After obtaining the models under study classification for each company and year, we proceeded to convert it by each models' parameters into Bankrupt and Non-Bankrupt, which were then converted into percentages concerning the total population of classifications.

By comparing the models' classification with the one previous attributed to each company in the seventh year (bankrupt or not), it was possible to validate the effectiveness of each model in correctly classifying the companies under study, arriving at the Type I and II errors (classification of bankrupt companies as not bankrupt and classification of non-bankrupt companies as bankrupt, respectively) and thus drawing up a ranking of the classification effectiveness attributed by the models studied for each of the years.

SUMMARY OF THE EFFECTIVENESS OF THE MODELS STUDIED

Table 5 shows the average classification efficiency of each of the models over all the years analyzed (wich is detailed by contry in the Appendix IV), highlighting the three most effective ones.

Table 5. Summary Table: Average Effectiveness of the Models and their Final Ranking

#	Global			Average	
	year	Author	Origen	Sucess	Place
1	1979	Altman, Baidya e Dias	Brazil	70%	10
2	1979	Altman, Baidya e Dias (2)	Brazil	57%	18
3	1980	Altman and Levallee	Canada	55%	20
4	1993	Altman	USA	71%	6
5	1995	Garcia, Arqués e Calvo-Flores	Spain	56%	19
6	1995	Garcia, Arqués e Calvo-Flores (2)	Spain	55%	21
7	1995	Garcia, Arqués e Calvo-Flores (3)	Spain	63%	16
8	1995	Altman, Hartzell e Peck	USA	62%	17
9	1997	Morgado	Portugal	70%	10
10	1998	Carvalho das Neves	Portugal	78%	3
11	1998	Lizarraga	Spain	73%	5
12	1998	Lizarraga (2)	Spain	68%	13
13	1998	Lizarraga (3)	Spain	81%	1
14	2011	Monelos, Sanchez e Lopez	Spain	65%	15
15	2011	Monelos, Sanchez e Lopez (2)	Spain	71%	6
16	2011	Monelos, Sanchez e Lopez (3)	Spain	80%	2
17	2014	López, Sánchez e Monelos	Spain	70%	9
18	2014	López, Sánchez e Monelos (2)	Spain	70%	8
19	2014	López, Sánchez e Monelos (3)	Spain	66%	14
20	2014	López, Sánchez e Monelos (4)	Spain	69%	12
21	2014	López, Sánchez e Monelos (5)	Spain	75%	4

Source: Own Elaboration

In Table 6, we compare the percentage of correct classification and respective errors of the base samples of each of the most effective models with those obtained from the application to the sample under study described in topic 7.

Table 6. Comparison Chart between the Base and Study Samples

			Average		Base	
	year	Author	Sucess	Place	Sucess	Diference
10	1998	Carvalho das Neves	78,3%	3	76,1%	2,2%
13	1998	Lizarraga (3)	80,5%	1	90,0%	-9,5%
16	2011	Monelos, Sanchez e Lopez (3)	79,6%	2	53,8%	25,8%

Source: Own Elaboration

CONCLUSIONS AND OPPORTUNITIES FOR IMPROVEMENT

It should be noted that the 21 multisectoral formulations that use the MDA technique and described in the topic 5, when applied to a sample of Portuguese and Spanish companies from the transport and storage sector (NACE H), those developed by Carvalho das Neves (1998), Lizarraga (1998) and Monelos et al. (2011) are the most effective at predicting corporate bankruptcy up to 6 years in advance.

As for the most effective models, the first one, Carvalho das Neves (1998), was commissioned by social security and developed based on a multi-sectoral sample with one year of data from 187 Portuguese companies where the healthy ones accounted for around 54%.

The other two were developed with similarly multisectoral, but Spanish samples. The second, Lizarraga (1998), used four years of data from 120 companies paired and equally distributed between healthy and bankrupt, while the third, Monelos et al. (2011), used the largest sample with 11 years of data and 372 companies, with healthy companies accounting for around 30%.

Some of the limitations mentioned in topic 3 were considered in the construction of the models studied. However, others remain to be so:

- Territorial sensitivity: we can assume that this issue was considered by the various authors since we didn't identify models with a sample of companies from several countries, but even though models from the respective nationalities of the companies studied emerged as the most efficient, no measures were identified by the respective authors in the model-building phases that would or not boost efficiency gains from this choice;
- Sector sensitivity: the use of multi-sectorial models built on samples that seek to portray the economy as a whole, as is the case with the formulations studied here, do reveal consistent levels of classification efficiency in the sector here studied;
- Temporal sensitivity: none of the models apply any specific treatment for the time gap between conception and usage;
- Sensitivity to the quality of information: as indicated in topic 2, the better the information used, the better the model will be. No special care has been taken with the information to be used, to guarantee the highest information quality, we selected companies subject to a statutory audit, as described in topic 7;
- Sensitivity to selection assumptions: all the models analyzed naturally select active companies as healthy. For bankrupt companies, they usually choose those which, in the period under analysis, have a Total equity < 0. The inclusion of differential sample separation parameters when training the models could prove beneficial.

In addition, we are witnessing the trivialization of the term bankruptcy, where failure to meet obligations to creditors is no longer regarded as a serious fault that carries heavy penalties, but rather as a simple misfortune or accident common to economic life.

Consequently, the techniques presented make a valuable contribution to predicting bankruptcy and helping to maintain stable economic conditions. However, we shouldn't overlook the possibilities for further research into the issues raised, which do have the potential to improve the models, making them more stable and widely applicable.

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APPENDIX I

Table 7. Different Ratios of the Used Models

1	Current Assets / Current Liabilities
2	Loans / Current Assets
3	Current Assets / Total Assets
4	Net Loan Costs / Sales
5	EBIT / Total Liabilities
6	(Current Assets – Inventory) / Current Liabilities
7	(Current Assets – Inventory – Current Assets) / Operational Expenses: (Sales – EBT – Adjustaments)
8	Net Profit / Total Assets
9	Working Capital / Total Assets
10	(Total Equity – Shareholder's Equity) / Total Assets
11	EBIT / Total Assets
12	Total Equity / Total Liabilities
13	Sales / Total Assets
14	Total Equity Growing Rate – Total Assets Growing Rate
15	EBIT / Net Financial Costs
16	Cash–flow / Total Assets
17	Net State Debt / Sales
18	Net Profit / Total Liabilities
19	Total Liabilities / Total Assets
20	Sector: construction = 1; other = 0
21	Colaterals: Yes = 1; No = 0
22	(Total Equity – Net Profit) / Current Liabilities
23	Sales / Cost of Goods Sold
24	Salaries / Non Current Assets
25	Depreciation / (Non Current Assets – Financial Investments)
26	(Net Profit – Current Assets + Cash) / Total Assets

Source: Own Elaboration

APPENDIX II

Table 8. Sub-sample of Failed Companies

Sub Sample Failed

Portugal

	Name	BvD ID	NACE Code	Actual Situation
1.	DSV TRANSITÁRIOS, LDA	PT500749345	H. Transportation and storage	Active
2.	MEDITERRANEAN SHIPPING COMPANY (PORTUGAL) - AGENTES DE NAVEGAÇÃO, S.A.	PT502614447	H. Transportation and storage	Active
3.	GENERAL LOGISTICS SYSTEMS PORTUGAL, LDA	PT507508688	H. Transportation and storage	Active
4.	URBANOS - SUPPLY CHAIN, S.A.	PT504808621	H. Transportation and storage	Active
5.	TRANSPORTES RODOVIÁRIOS ESTRELA DO MONTE DA CAPARICA, S.A.	PT500289450	H. Transportation and storage	Active
6.	RENEX - REDE NACIONAL DE TRANSPORTES, LDA	PT500572550	H. Transportation and storage	Active
7.	EMTRAL - EMPRESA TRANSPORTES DE ALUGUER, LDA	PT501855394	H. Transportation and storage	Active
8.	TRANSPORTES NOVA CRUZ, LDA	PT504315153	H. Transportation and storage	Active
9.	ALBERTO FERNANDES & FERNANDES, LDA	PT503566896	H. Transportation and storage	Active
10.	RED QUEEN NAVIGATION - TRANSPORTES MARÍTIMOS, SOCIEDADE UNIPESSOAL, LDA	PT511162006	H. Transportation and storage	Temporarily Inactive
11.	FOUR VANGUARD - SERVIÇOS E NAVEGAÇÃO, SOCIEDADE UNIPESSOAL, LDA (ZONA FRANCA DA MADEIRA)	PT511115377	H. Transportation and storage	Active

Spain

	Nome	BvD ID	NACE Code	Actual Situation
1.	GROUPE LOGISTICS IDL ESPAÑA SA	ESA84320928	H. Transportation and storage	Active
2.	TOURLINE EXPRESS MENSAJERIA SL	ESB63238455	H. Transportation and storage	Active
3.	NACIONAL 10 HORAS S L	ESB79491601	H. Transportation and storage	Activa (insolvency proceedings)
4.	AUTOPISTA DEL SURESTE CONCESIONARIA ESPAÑOLA DE AUTOPISTAS SA	ESA82128455	H. Transportation and storage	Active
5.	VANGUARD LOGISTICS SERVICES SA	ESA64332380	H. Transportation and storage	Active
6.	TRANSCOMA CRUISE & TRAVEL SL	ESB65218760	H. Transportation and storage	Active
7.	ATLANTICO SHIPPING SL	ESB15128457	H. Transportation and storage	Active
8.	AUTOCARES DISCRECIONALES DEL NORTE SOCIEDAD LIMITADA	ESB09007113	H. Transportation and storage	Active
9.	FRIO EL PILAR SL	ESB04312278	H. Transportation and storage	Activa (insolvency proceedings)
10.	ECULINE SPAIN SL	ESB60445426	H. Transportation and storage	Active
11.	OSTALE SL	ESB41031725	H. Transportation and storage	Active

Source: Own Elaboration

APPENDIX III

Table 9. Sub-sample of Non-Failed Companies

Sub Sample Non-Failed

Portugal

	Name	BvD ID	NACE Code	Actual Situation
1.	TRANSPORTES BERNARDO MARQUES, LDA	PT502737565	H. Transportation and storage	Active
2.	TCGL - TERMINAL DE CARGA GERAL E DE GRANÉIS DE LEIXÕES, S.A.	PT505046261	H. Transportation and storage	Active
3.	TRANSPORTES MACHADO & BRITES, LDA	PT500975850	H. Transportation and storage	Active
4.	BENTRANS - CARGA E TRANSITÁRIOS, S.A.	PT512013403	H. Transportation and storage	Active
5.	PORTSINES - TERMINAL MULTIPURPOSE DE SINES, S.A.	PT502517549	H. Transportation and storage	Active
6.	TIEL - TRANSPORTES E LOGÍSTICA, S.A.	PT501104178	H. Transportation and storage	Active
7.	VARELA & CA., LDA	PT512004854	H. Transportation and storage	Active
8.	RODONORTE - TRANSPORTES PORTUGUESES, S.A.	PT500095914	H. Transportation and storage	Active
9.	FORCARGO - TRANSPORTES, S.A.	PT503735744	H. Transportation and storage	Active
10.	PORTO SANTO LINE - TRANSPORTES MARÍTIMOS, LDA	PT511035543	H. Transportation and storage	Active
11.	UNIÃO DE TRANSPORTES DOS CARVALHOS, LDA	PT500292566	H. Transportation and storage	Active
12.	RODOVIÁRIA DA BEIRA INTERIOR, S.A.	PT502526483	H. Transportation and storage	Active
13.	FROTA AZUL (ALGARVE) - TRANSPORTES E TURISMO, LDA	PT500059136	H. Transportation and storage	Active
14.	RESENDE - ACTIVIDADES TURÍSTICAS, S.A.	PT500269165	H. Transportation and storage	Active
15.	TRANSPORTES HEITOR & CARLOS, LDA	PT504633503	H. Transportation and storage	Active
16.	VALPI BUS - ALBERTO PINTO & FILHOS, TRANSPORTES RODOVIÁRIOS, S.A.	PT500728348	H. Transportation and storage	Active
17.	REBOPORT - SOCIEDADE PORTUGUESA DE REBOQUES MARÍTIMOS, S.A.	PT504409425	H. Transportation and storage	Active
18.	URBANOS - SOLUÇÕES, S.A.	PT502392290	H. Transportation and storage	Active

Spain

	Name	BvD ID	NACE Code	Actual Situation
1.	AUTOBUSES URBANOS DE BILBAO SOCIEDAD ANONIMA.	ESA95524823	H. Transportation and storage	Active
2.	AUTOBUSES URBANOS DE VALLADOLID SA	ESA47028378	H. Transportation and storage	Active
3.	MARCO Y SANCHEZ TRANSPORTES URBANOS SOCIEDAD ANONIMA	ESA03024973	H. Transportation and storage	Active
4.	LA HISPANO DE FUENTE EN SEGURES SA	ESA12000071	H. Transportation and storage	Active
5.	FOMENT DEL RECICLATGE SA	ESA61868147	H. Transportation and storage	Active
6.	COMPAÑIA IBERICA DE REMOLCADORES DEL ESTRECHO SA	ESA41020579	H. Transportation and storage	Active
7.	DOCKS LOGISTICS SPAIN SOCIEDAD ANONIMA	ESA81395220	H. Transportation and storage	Active
8.	TRANSPORTES MARGUT SA	ESA39050497	H. Transportation and storage	Active
9.	GREEN IBERICA SL	ESB58002858	H. Transportation and storage	Active
10.	CONTINENTAL PARKING SL	ESB58161514	H. Transportation and storage	Active
11.	SERTOSA NORTE SL	ESB48990766	H. Transportation and storage	Active
12.	MANIPULADORA DE MERCANCIAS SL	ESB08149676	H. Transportation and storage	Active
13.	ARRIVA GALICIA SL.	ESB82387176	H. Transportation and storage	Active
14.	TRANSALINETAS LOGISTIC SL	ESB35576909	H. Transportation and storage	Active
15.	RECEPTORA DE LIQUIDOS SA	ESA08145385	H. Transportation and storage	Active
16.	REMOLCADORES DE BARCELONA, SA	ESA08010977	H. Transportation and storage	Active
17.	ARGABUS SA	ESA28099356	H. Transportation and storage	Active
18.	LOS AMARILLOS SL	ESB41000134	H. Transportation and storage	Active

Source: Own Elaboration

APPENDIX IV

Table 10. Average Effectiveness of the Models and their Final Ranking

Portugal

#	year	Author	Origen	n Sucess	n Place	n-1 Sucess	n-1 Place	n-2 Sucess	n-2 Place	n-3 Sucess	n-3 Place	n-4 Sucess	n-4 Place	n-5 Sucess	n-5 Place	n-6 Sucess	n-6 Place	Average Sucess	Average Place
1	1979	Altman, Baidya e Dias	Brazil	83%	5	76%	5	76%	3	72%	5	69%	8	62%	9	66%	8	**72%**	**6**
2	1979	Altman, Baidya e Dias (2)	Brazil	66%	16	66%	15	55%	19	48%	18	52%	18	45%	19	48%	18	**54%**	**19**
3	1980	Altman and Levallee	Canada	41%	21	69%	11	66%	11	41%	19	55%	17	59%	11	52%	17	**55%**	**18**
4	1993	Altman	USA	79%	9	76%	5	72%	5	69%	7	72%	5	59%	11	69%	4	**71%**	**7**
5	1995	Garcia, Arqués e Calvo-Flores	Spain	48%	19	45%	20	41%	20	41%	19	38%	21	41%	20	41%	20	**42%**	**21**
6	1995	Garcia, Arqués e Calvo-Flores (2)	Spain	48%	19	45%	20	41%	20	41%	19	41%	20	38%	21	41%	20	**42%**	**20**
7	1995	Garcia, Arqués e Calvo-Flores (3)	Spain	66%	16	62%	16	59%	18	55%	16	52%	18	48%	18	48%	18	**56%**	**17**
8	1995	Altman, Hartzell e Peck	USA	62%	18	62%	16	62%	15	62%	14	62%	13	62%	9	62%	11	**62%**	**15**
9	1997	Morgado	Portugal	79%	9	69%	11	72%	5	72%	5	69%	8	66%	5	62%	11	**70%**	**9**
10	1998	Carvalho das Neves	Portugal	93%	1	93%	1	76%	3	83%	1	83%	1	76%	1	76%	2	**83%**	**1**
11	1998	Lizarraga	Spain	76%	13	76%	5	69%	7	66%	11	72%	5	59%	11	66%	8	**69%**	**10**
12	1998	Lizarraga (2)	Spain	76%	13	69%	11	62%	15	52%	17	62%	13	52%	17	62%	11	**62%**	**15**
13	1998	Lizarraga (3)	Spain	86%	2	93%	1	69%	7	69%	7	83%	1	69%	4	72%	3	**77%**	**3**
14	2011	Monelos, Sanchez e Lopez	Spain	79%	9	72%	8	69%	7	69%	7	69%	8	66%	5	69%	4	**70%**	**8**
15	2011	Monelos, Sanchez e Lopez (2)	Spain	83%	5	69%	11	79%	2	83%	1	79%	4	66%	5	69%	4	**75%**	**4**
16	2011	Monelos, Sanchez e Lopez (3)	Spain	86%	2	90%	3	83%	1	79%	3	83%	1	76%	1	79%	1	**82%**	**2**
17	2014	López, Sánchez e Monelos	Spain	86%	2	72%	8	66%	11	66%	11	62%	13	59%	11	62%	11	**67%**	**11**
18	2014	López, Sánchez e Monelos (2)	Spain	79%	9	72%	8	66%	11	62%	14	59%	16	59%	11	62%	11	**66%**	**13**
19	2014	López, Sánchez e Monelos (3)	Spain	72%	15	62%	16	69%	7	66%	11	66%	11	66%	5	66%	8	**67%**	**12**
20	2014	López, Sánchez e Monelos (4)	Spain	83%	5	62%	16	62%	15	69%	7	66%	11	59%	11	59%	16	**66%**	**13**
21	2014	López, Sánchez e Monelos (5)	Spain	83%	5	79%	4	66%	11	76%	4	72%	5	72%	3	69%	4	**74%**	**5**

Spain

#	year	Author	Origen	n Sucess	n Place	n-1 Sucess	n-1 Place	n-2 Sucess	n-2 Place	n-3 Sucess	n-3 Place	n-4 Sucess	n-4 Place	n-5 Sucess	n-5 Place	n-6 Sucess	n-6 Place	Average Sucess	Average Place
1	1979	Altman, Baidya e Dias	Brazil	83%	5	73%	5	70%	10	57%	17	53%	15	57%	14	70%	10	**66%**	**14**
2	1979	Altman, Baidya e Dias (2)	Brazil	63%	18	67%	13	57%	21	57%	17	50%	18	60%	8	57%	20	**59%**	**19**
3	1980	Altman and Levallee	Canada	57%	21	47%	21	67%	11	50%	21	43%	21	57%	14	53%	21	**53%**	**21**
4	1993	Altman	USA	77%	10	73%	5	67%	11	60%	12	60%	7	70%	1	70%	10	**68%**	**10**
5	1995	Garcia, Arqués e Calvo-Flores	Spain	77%	10	73%	5	67%	11	70%	4	60%	7	60%	8	63%	16	**67%**	**13**
6	1995	Garcia, Arqués e Calvo-Flores (2)	Spain	73%	14	70%	11	63%	15	70%	4	60%	7	57%	14	60%	18	**65%**	**15**
7	1995	Garcia, Arqués e Calvo-Flores (3)	Spain	73%	14	73%	5	60%	17	73%	1	63%	3	67%	4	67%	13	**68%**	**10**
8	1995	Altman, Hartzell e Peck	USA	60%	19	60%	19	60%	17	60%	12	60%	7	60%	8	60%	18	**60%**	**18**
9	1997	Morgado	Portugal	77%	10	67%	13	67%	11	70%	4	60%	7	63%	7	73%	9	**68%**	**10**
10	1998	Carvalho das Neves	Portugal	90%	2	77%	3	77%	2	60%	12	53%	15	60%	8	83%	8	**71%**	**6**
11	1998	Lizarraga	Spain	83%	5	80%	2	77%	2	73%	1	70%	1	70%	1	70%	10	**75%**	**2**
12	1998	Lizarraga (2)	Spain	77%	10	73%	5	73%	8	70%	4	67%	2	70%	1	67%	13	**71%**	**7**
13	1998	Lizarraga (3)	Spain	90%	2	93%	1	87%	1	73%	1	63%	3	67%	4	93%	1	**81%**	**1**
14	2011	Monelos, Sanchez e Lopez	Spain	60%	19	60%	19	60%	17	53%	19	50%	18	53%	18	67%	13	**58%**	**20**
15	2011	Monelos, Sanchez e Lopez (2)	Spain	73%	14	67%	13	63%	15	53%	19	50%	18	53%	18	87%	7	**64%**	**16**
16	2011	Monelos, Sanchez e Lopez (3)	Spain	93%	1	77%	3	77%	2	60%	12	53%	15	67%	4	93%	1	**74%**	**3**
17	2014	López, Sánchez e Monelos	Spain	83%	5	67%	13	77%	2	63%	11	60%	7	53%	18	93%	1	**71%**	**7**
18	2014	López, Sánchez e Monelos (2)	Spain	83%	5	70%	11	77%	2	67%	8	63%	3	57%	14	93%	1	**73%**	**5**
19	2014	López, Sánchez e Monelos (3)	Spain	67%	17	67%	13	60%	17	60%	12	60%	7	60%	8	63%	16	**62%**	**17**
20	2014	López, Sánchez e Monelos (4)	Spain	83%	5	63%	18	73%	8	67%	8	60%	7	50%	21	90%	6	**70%**	**9**
21	2014	López, Sánchez e Monelos (5)	Spain	87%	4	73%	5	77%	2	67%	8	63%	3	60%	8	93%	1	**74%**	**3**

Global

#	year	Author	Origen	n Sucess	n Place	n-1 Sucess	n-1 Place	n-2 Sucess	n-2 Place	n-3 Sucess	n-3 Place	n-4 Sucess	n-4 Place	n-5 Sucess	n-5 Place	n-6 Sucess	n-6 Place	Average Sucess	Average Place
1	1979	Altman, Baidya e Dias	Brazil	84%	6	76%	6	74%	4	66%	9	62%	12	60%	11	69%	10	**70%**	**10**
2	1979	Altman, Baidya e Dias (2)	Brazil	66%	17	67%	14	57%	19	53%	20	52%	18	53%	19	53%	18	**57%**	**18**
3	1980	Altman and Levallee	Canada	50%	21	59%	20	67%	14	47%	21	50%	20	59%	14	53%	18	**55%**	**20**
4	1993	Altman	USA	79%	10	76%	6	71%	10	66%	9	67%	6	66%	5	71%	9	**71%**	**6**
5	1995	Garcia, Arqués e Calvo-Flores	Spain	64%	18	60%	19	55%	20	57%	18	50%	20	52%	20	53%	18	**56%**	**19**
6	1995	Garcia, Arqués e Calvo-Flores (2)	Spain	62%	19	59%	20	53%	21	57%	18	52%	18	48%	21	52%	21	**55%**	**21**
7	1995	Garcia, Arqués e Calvo-Flores (3)	Spain	71%	14	69%	11	60%	18	66%	9	59%	17	59%	14	59%	17	**63%**	**16**
8	1995	Altman, Hartzell e Peck	USA	62%	19	62%	18	62%	17	62%	15	62%	12	62%	9	62%	16	**62%**	**17**
9	1997	Morgado	Portugal	79%	10	69%	11	71%	10	72%	1	66%	7	66%	5	69%	10	**70%**	**10**
10	1998	Carvalho das Neves	Portugal	93%	1	86%	2	78%	3	72%	1	69%	3	69%	2	81%	4	**78%**	**3**
11	1998	Lizarraga	Spain	81%	9	79%	4	74%	4	71%	5	72%	2	66%	5	69%	10	**73%**	**5**
12	1998	Lizarraga (2)	Spain	78%	13	72%	8	69%	12	62%	15	66%	7	62%	9	66%	14	**68%**	**13**
13	1998	Lizarraga (3)	Spain	90%	3	95%	1	79%	2	72%	1	74%	1	69%	2	84%	2	**81%**	**1**
14	2011	Monelos, Sanchez e Lopez	Spain	71%	14	67%	14	66%	15	62%	15	60%	16	60%	11	69%	10	**65%**	**15**
15	2011	Monelos, Sanchez e Lopez (2)	Spain	79%	10	69%	11	72%	6	69%	7	66%	7	60%	11	79%	5	**71%**	**6**
16	2011	Monelos, Sanchez e Lopez (3)	Spain	91%	2	84%	3	81%	1	71%	5	69%	3	72%	1	88%	1	**80%**	**2**
17	2014	López, Sánchez e Monelos	Spain	86%	4	71%	10	72%	6	66%	9	62%	12	57%	17	79%	5	**70%**	**9**
18	2014	López, Sánchez e Monelos (2)	Spain	83%	8	72%	8	72%	6	66%	9	62%	12	59%	14	79%	5	**70%**	**8**
19	2014	López, Sánchez e Monelos (3)	Spain	71%	14	66%	16	66%	15	64%	14	64%	10	64%	8	66%	14	**66%**	**14**
20	2014	López, Sánchez e Monelos (4)	Spain	84%	6	64%	17	69%	12	69%	7	64%	10	55%	18	76%	8	**69%**	**12**
21	2014	López, Sánchez e Monelos (5)	Spain	86%	4	78%	5	72%	6	72%	1	69%	3	67%	4	83%	3	**75%**	**4**

Source: Own Elaboration