AESTIMATIO, THE IEB INTERNATIONAL JOURNAL OF FINANCE, 2017. **14**: 108-131 DOI:10.5605/IEB.14.6

The use of multivariate discriminant analysis to predict corporate bankruptcy: A review

Peres, Cândido
Antão, Mário

RECEIVED: 24 JUNE 2016
ACCEPTED: 23 SEPTEMBER 2016

Abstract

The ongoing and increasingly devastating global financial crisis makes it ever more crucial to understand the causes of business failure, epitomized in the concept of "bankruptcy", with a particular emphasis on its prediction and anticipation. Although one "bankruptcy" event may differ significantly from another, and not just in terms of differences relating to geography or activity sectors, there tend to be some common difficulties and limitations in its prediction. This article presents a review of the applications of multivariate discriminant analysis to the prediction of business "bankruptcy". We collected 123 functions or discriminant models, developed or revised by researchers between 1968 and 2014, for various time horizons, countries and sectors. We aim to identify the procedures and common features of these analyses, the main constraints they faced and the measures taken by the authors to ensure optimum conditions for the stability and effectiveness of the models. This article thus suggests opportunities for improving the performance of discriminant models, in terms of the data used and its treatment.

Keywords:

Multivariate discriminate analysis, Corporate bankruptcy, Prediction models, Forecast.

JEL classification:

G17, G31, G33.

Please cite this article as:

Peres, C. and Antão, M. (2017). The use of multivariate discriminant analysis to predict corporate bankruptcy: A review *AESTIMATIO, The IEB International Journal of Finance,* **14***,* pp. 108-131.

doi: 10.5605/IEB.14.6

Peres M., C. J. ✉ Instituto Superior de Contabilidade e Administração de Lisboa, Instituto Politécnico de Lisboa, Avenida Miguel Bombarda, No. 20, 1069-035 Lisboa, Portugal. ✆ +351-916941177. E-mail: cjperes@iscal.ipl.pt.

Antão, M.A. - Faculdade de Ciências da Economia e da Empresa, Universidade Lusíada de Lisboa, Rua da Junqueira, No. 188-198, 1349-001 Lisboa, Portugal. ✆ +351-917543270. E-mail: maga@lis.ulusiada.pt.

AESTIMATIO, THE IEB INTERNATIONAL JOURNAL OF FINANCE, 2017. **14**: 108-131

El uso del análisis discriminante multivariante en la predicción de la quiebra empresarial: **Una revisión**

Peres, Cândido

Antão, Mário

Resumen

La recurrente crisis mundial cada vez más devastadora vuelve a poner de actualidad la búsqueda de las causas de la destrucción de empresas, cuestión encarnada en el concepto de "quiebra", y en particular en su predicción y anticipación. A pesar de las características de la “quiebra” empresarial son diferentes, independientemente de la geografía o sector, su predicción comparte dificultades y limitaciones similares. En este artículo se presenta una revisión de las aplicaciones del análisis discriminante multivariante en el ámbito de la predicción de la quiebra empresarial. Se analizan 123 funciones o modelos discriminantes, revisados o desarrollados por los investigadores entre 1968 y 2014, para múltiples horizontes temporales, países y sectores de actividad. Se identifican las características que tienen en común y sus principales restricciones, así como las medidas adoptadas por los autores para garantizar las mejores condiciones para la estabilidad y eficacia de los modelos. Este artículo sugiere algunas oportunidades de mejora en el rendimiento de los modelos discriminantes, de acuerdo con los datos usados y su tratamiento.

Palabras clave:

Análisis discriminante multivariante, quiebra empresarial, modelos de predicción, previsión.

1. Introduction

In recent years, our financial world has become very different from the one in place since the recovery from the Great Depression of 1929.

In 2007, a financial crisis caused the world economy to once again hit rock bottom. At the root of this subprime crisis was financial institutions' readiness to approve low quality credits, such as the NINJA type loans. This crisis, considered by many as the worst in the history of capitalism since 1929, brought on a prolonged and deep economic contraction, directly or indirectly affecting all sectors of activity and countries.

The Greek government-debt crisis, the bailouts of other various European countries and the liquidity support provided to banks and other financial institutions all over the world, highlighted the need to anticipate and predict these situations to allow timely contingency measures to be taken to prevent them, or at least to mitigate the adverse effects.

Over the past decades, ever since the preliminary work of Beaver (1966) in applying univariate analysis to "bankruptcy" prediction, followed by Altman (1968) and his multivariate discriminant analysis, numerous different authors have developed techniques and models for this purpose. From the simplest to the most complex we find extensive attempts to predict business "bankruptcy" —some, of course, more successful than others.

Of all the techniques applied and developed in nearly 50 years of business "bankruptcy" study and prediction, it is worth highlighting the aforementioned multivariate discriminant analysis for its enduring applicability, simplicity and effectiveness. Despite its limitations, no other model type has yet been identified which combines its simplicity in terms of managing, interpreting and applying it, and offers similar levels of classification efficiency. There are a number of articles with a similar aim to ours. Zavgren (1983) and Altman (1984) provide a review of the statistical models but with less detail than we intend to provide here.

More recently, a number of other, similar articles have been written; namely, those of Fernández and Gutiérrez (2012), Jackson and Wood (2013) and Sun *et al.* (2014), as well as the most widely referenced papers in the literature, which are Aziz and Dar (2004), Bellovary *et al.* (2007) and Pereira *et al.* (2010). Those studies, despite identifying numerous models, cover all the business "bankruptcy" forecasting techniques in the same analysis. Doing so naturally limits the number of models contained in the study and also reduces the individual focus on each of the techniques, which could then lead to less objective conclusions.

It should be pointed out that, in this article, the word "bankruptcy" always appears between quotation marks since there is no full consensus in the literature as to the meaning of the term. Definitions range from a company's inability to meet its commitments, to a simple calculation of Assets < Liabilities. We thus use quotation marks in this article to indicate our acceptance of the plurality of meanings commonly assigned to this term.

This article aims to provide an exhaustive survey of applicable models, including their features, advantages and limitations, as well as the opportunities for improvement and optimization, as well as focusing on a single technique that may or may not have different kinds of results when applied to different types of companies, activity sectors or countries. To that end, the article is organized as follows: after this brief introduction, section 2 is devoted to the main approaches to business "bankruptcy" prediction; section 3 focuses on discriminant analysis; section 4 addresses the issue of how to read the indicators used in the discrimination process; section 5 details the main characteristics of the discriminant models used in the literature surveyed; and section 6 outlines the conclusions and some opportunities for improvement.

2. Main approaches and model types: Characteristics and limitations

Several authors indicate that the first studies on business "bankruptcy" prediction emerged in the US in the 1930s, following the Great Depression. However, according to Divsalar *et al.* (2011), interest in this subject only gained real momentum from the 1960s onwards, with the application of statistical techniques.

There are numerous studies on business "bankruptcy" and, in particular, "bankruptcy" prediction. In response, Aziz and Dar (2004), Bellovary *et al.* (2007), Pereira et al. (2010), Fernández and Gutiérrez (2012), Jackson and Wood (2013) and Sun *et al.* (2014) suggest the following grouping for the types of business "bankruptcy" prediction models:

2.1. Statistical approach

Historically, this was the first type of model to emerge, typically being simple, easy and quick to use. Although research on this subject began in the 1930s, the first univariate analysis model appears in Beaver's 1966 study, which used a set of indicators applied successively and separately to classify a company as being healthy or not.

However, this approach had some inherent limitations. Altman (1968, p. 591) gave an example of this issue, stating that "a firm with a poor profitability and/or solvency record may be regarded as a potential bankrupt. However, because of its above average liquidity, the situation may not be considered serious". Along the same lines, Divsalar *et al.* (2011) argues that different ratios can move in opposite directions, thus producing different predictions.

A natural evolution led to the extension of the univariate analysis by simultaneously considering several factors. According to Bellovary *et al.* (2007, p. 4), Beaver, in his suggestions for future research, "indicated the possibility that multiple ratios considered simultaneously may have higher predictive ability than single ratios – and so began the evolution of bankruptcy prediction models."

Thus, in 1968 Altman combined several indicators in one discriminating function, demonstrating a strong improvement to the forecast, creating the Z-Score model and, with it, the application of multivariate discriminant analysis (MDA), demonstrating a marked improvement in prediction accuracy.

According to Altman (1968, p. 592), MDA has "the advantage of considering an entire profile of characteristics common to the relevant firms, as well as the interaction of these properties". This is not a perfect technique, however, and is subject to certain assumptions and limitations.

MDA assumes that the variables of the sample, i.e., the financial indicators to be used, have a normal distribution and, furthermore, that the company under analysis is comparable to the one originally used to estimate the model. Obviously, the better the information it uses, the better the results. Prediction capability may be reduced by the existence of differences in accounting treatment, issues of creative accounting, and by the fact that companies in financial difficulties tend to delay the disclosure of their financial information.

Since the appearance of these methods which marked the beginning of "bankruptcy" prediction research, many researchers have explored and addressed these issues. According to Sun *et al.* (2014) among others, the predictive power of MDA the year before "bankruptcy" is significantly better than that of the single variable discriminant model.

The Statistical approach includes not only the univariate and multivariate versions of discriminant analysis, but also the partial least squares discriminant analysis, logit, probit, cumulative sum control charts and the survival analysis, among others.

2.2. Artificial Intelligence Expert Systems (AIES)

The availability of computers and technological advances, especially since the 1980s, has led to the creation of technological models. AIES emerged as an alternative to the classic Statistical approach models that had already been in use for a long time. Computers can simulate human cognitive intelligence and behaviour in problem-solving issues. This finding prompted a search for programs that could adequately simulate these human skills, giving rise in the 1950s to the field of research that became known as "Artificial Intelligence" (AI).

Humans use their intelligence to solve problems, applying reasoning based on their knowledge and experience, both of which play a central role in human intelligence. In order to recreate human intelligence, AI should take advantage of such knowledge in its application of reasoning to the problem in question, and Expert Systems (ES) have been developed to address this matter. This approach include neural networks, support vector machine, evolution algorithms, case-based reasoning, rough set and decision trees, among others.

2.3. Theoretical approach

This is one of the most recent approaches to emerge, based on a criticism of the main focus of the Statistical and AIES models. According to the critics, since these latter models are built without any theoretical basis, they focus on the symptoms of business "bankruptcy" rather than on its causes. Predicting business "bankruptcy" without a theoretical support has long been questioned, leading researchers to try to underpin their explanations of the process of "bankruptcy" with theory.

In other words, Statistical and AIES approach models are able to predict "bankruptcy" by examining the empirical stress conditions present in the companies under study. However, another way to approach this problem is to look at the factors that theoretically lead companies to "bankruptcy".

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

In brief, after the initial use of conventional statistical techniques, as mentioned above, the AIES models appeared and used characteristics of both univariate and multivariate Statistical methodologies. Therefore, the AIES models are considered little more than an automation of the Statistical approach. On the contrary, the models built on a theoretical base do not necessarily try to establish the modelling technique first, but rather try to model the argument using an appropriate statistical technique. Thus, even the Theoretical approach models seem to have benefited from statistical techniques in general, meaning that the role of the Statistical approach models within the Theoretical approach should not be overlooked.

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According to Bellovary *et al.* (2007) among others, it is easy to identify that statistical techniques have long been used in all types of business "bankruptcy" prediction models (since 1968), with the main methods used being MDA, logit and probit analysis. These latter methods appeared in the 1970s and managed to eliminate some of the more rigid assumptions to which the former are subject, although they did not surpass the former model in terms of efficiency and popularity.

In addition to the abovementioned systematized facts of the various techniques developed over the years to predict business "bankruptcy", there are other studies that have provided reviews of "bankruptcy" prediction models.

Some such studies include Aziz and Dar (2004), Bellovary *et al.* (2007), Pereira *et al.* (2010), Fernández and Gutiérrez (2012), Jackson and Wood (2013) and Sun *et al.* (2014), which focus specifically on classification efficiency, frequency of use over time and number of previously listed techniques.

These studies can be used as guides to help us select the technique that best suits our aims. They show the prominence of MDA in that it is clearly more widely referenced and is more frequently researched.

Furthermore, it seems to us that the research path to follow is that recommended by Bellovary *et al.* (2007, p. 12), who suggest that "the focus of future research should be on the use of existing bankruptcy prediction models as opposed to the development of new models [...] Future research should consider how these models can be applied and, if necessary, refined."

3. Discriminant analysis

As a Statistical approach, discriminant analysis detects the distinctive attributes of the elements of one group that distinguish them from the ones belonging to another. Based on these different characteristics, it is then possible to predict which group any new element will belong to.

After being formulated and applied, this method will essentially tell us if the features of the company under analysis are more similar to the elements belonging to group A ("bankruptcy") or B (not "bankruptcy").

From a technical point of view, it is assumed that the data follows a normal multivariate distribution, although the violation of this assumption does not generally have serious implications. It is also assumed that the variance/covariance matrices are homogeneous among the groups; however, small deviations are not particularly important so, in many cases, the analysis remains valid even without strict compliance with these assumptions.

Since this is the most extensively-studied technique, it is also easier to see its limitations. Like any other method, its performance is heavily dependent on the data available for the training sample. This means that it can be affected by, among other things the reliability of the financial statements used to calculate its independent variables. Besides that, it is also:

- Territorially Sensitive: a model designed for a particular country, area or region will have a potentially different performance when applied to a different geographical location. Countries differ from one another in terms of their legal requirements, accounting, tax and labour systems, ease or difficulty of access to credit, characteristics of their financial systems and, ultimately, macro and microeconomics policies, cultural issues and tradition, all of which also affect management style;

- Sectorial Sensitive: each sector of the economy has specific features, from the performance in their financial indicators to the intrinsic characteristics of its operation. For example, the hotel and catering sector includes both 5-star hotels and small restaurants, which have very different structures and indicators; however, there is an even greater difference with a heavy industry or a service company. It is clear that there are financial ratios or indicators that behave in a specific way depending on the sector; a model that does not take this issue into account and lumps different industries or economic sectors together could exclude certain indicators that, although they may not be good predictors for some sectors, may well be for others;

- Time Sensitive: A model designed in the mid-twentieth century is unlikely to yield the same classification performance now when applied to a present day sample of companies, even if the companies were from the same country and sector, and were of similar size and characteristics to the ones used to design the model in first place. The business landscape has changed substantially since the last century and there have also been developments in information reporting systems and in the accounting treatment of certain ammounts, such as goodwill research and development (R&D) expenses, as well as other options for the capitalization of expenses;

- Sensitive to bias in the sample selection: non-random sampling, where the analyst does not apply any specific treatment or selects the entire population results in the inclusion of more cases of one type than the other (healthy or failed) in the model training or building phase. Naturally, developing a model from a sample that has more of one group than the other could cause it to be biased later when it comes to ranking companies;

- Sensitive to selection assumptions: in addition to all the previous sensitivities, the model is also defined by the analyst's opinion on the financial ratios or indicators that should or should not be included in the model, as well as the assumptions the analyst makes in terms of tests to be carried out, segmentations to be made and other measures to be implemented to address the issues that arise.

4. Economic and financial analysis and the reading of indicators

Characteristics that can be inferred from the indicators contained in a company's accounting information include the financial health of the company, its performance and stakeholders' perception of it. According to Brealey and Myers (2010), financial analysis is generally seen as a key to revealing what is hidden in the accounting information, but it is not, by itself, a crystal ball; as Brealey *et al.* (2001) and Ross *et al.* (2002) argue, it is simply the summarizing of a large amount of financial information which then helps analysts to ask the right questions and facilitates comparisons between years and companies.

We can take a narrow view of financial analysis and see only the relationship between the balance sheet items or between the budged execution level 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 former relates to the requirements of the company's financial department and the latter concerns the entities that, in one way or another, deal with the company (suppliers, banks, creditors in general, customers, investors, etc.).

Financial analysis is, of course, heavily dependent on how the accounting information is disclosed. Each country has its own way of making such information available: some have accounting standards closely linked to tax requirements, others less so; some incorporate more international standards, others fewer.

Overtime, regulations have been defined and redefined to help create a more rigorous regulatory environment. Nevertheless, companies still have some freedom to decide how to report their results (closely or more loosely related to the tax criteria, more or less effective validation of the going concern, etc...) and in the decision of what to show in the balance sheet. That said, effective financial analysis requires the analyst to go beyond appearances and attempt to understand some of the decisions taken by those responsible for the company's accounting.

In order to reduce the risk of using accounting items that may contain inaccuracies or distortions of the company's true economic and financial position, Breia (2013) suggests using a red flag indicators technique.

These red flags, identified through a critical reading of the accounting information (articulating values, identifying trends, comparing, testing the coherence, consistency and reasonableness of the information presented), may reveal inconsistencies. Such discrepancies may not be clear evidence of irregularity but rather represent situations that, when compared with the standards of the company itself or of its activity sector, show significant variations or strongly dissimilar values.

The following situations may raise some potential red flags, and should thus be carefully examined to determine the causes:

1. Reporting high figures for cash and its equivalents (bank balances or equivalent) simultaneously with high-interest-bearing liabilities; if this situation continues for long periods of time it can reveal financial inefficiency;

2. Very long turnaround times for receivables or inventory rotation may reveal, among other things, risks not covered by impairment charges, over-invoicing, collection difficulties or sub-optimal conditions for sales;

3. Investments without visibly adequate returns (recorded via the equity method and without recording impairments);

4. Very low average rates of depreciation/amortization of assets or of provisions or impairments (both in comparison to the past activity of the company and to the activity sector as a whole), may be indicative of deceleration and subsequent results manipulation;

5. Instability in the asset depreciation or amortization criteria may be indicative of an attempt to manipulate results;

6. Non justified large increases or reductions of provisions or impairments from one year to the next may also indicate results manipulation;

7. Deferred tax assets related to losses that are subject to tax reporting and lack of clear evidence of taking appropriate measures to restructure the company to allow these losses to be recovered.

However, according to Breia (2012), it should be noted that there are situations, which do not necessarily involve any wrongdoing or irregularities, where the choices made by management improve—in some cases significantly—the firm's economic and financial position and, consequently, its results and financial performance, namely:

a) Use of operating leases instead of pure leasing will reduce Assets and consecutively improve performance indicators for asset rotation in relation to sales, and returns on net and operating assets;

b) Dilution of investments (holdings of less than 20% may not require the application of the equity method);

c) Assets dation as payment to a creditor bank. With those assets subsequently being passed to a leasing fund, thus reducing Assets and debt and consequently improving various indicators relating to these items;

d) Negotiated extension of payment terms to suppliers, with no additional cost, will increase the cyclical resources;

e) Aggressive liquidation policies for Inventories or account receivables (particularly at the end of the year), leading to improved performance in various indicators including inventory rotation or payment of clients and, consequently, reducing the cyclical needs;

f) Intensive use of debt refinancing, such as factoring operations, which will improve the performance of some indicators and the balance sheet itself;

g) Treatment of shareholders' input funds (complementary) as Equity rather than Liabilities can improve the performance of indicators relating to Liabilities and Equity.

5. Models analysed

We attempted to explore changes in "bankruptcy" prediction over time, to identify similarities and differences, as well as the most common intrinsic characteristics of the Statistical models, particularly MDA ones. We thus collected the models created, recalculated or readjusted applying this technique that are most widely referenced in the literature. To this end, we focus particularly on those detailed by Aziz and Dar (2004), Bellovary *et al.* (2007), Pereira *et al.* (2010), Fernández and Gutiérrez (2012), Jackson and Wood (2013) and Sun *et al.* (2014), in addition to a number of other authors that had published their work internationally. From this, we were able to identify a total of 123 different formulations (which we refer to as "General") from the period 1968-2014. Of those, 61 were published in major scientific journals rated for impact factor (which we refer to as "Peer Reviewed").

Table 1. Number of surveyed models by country

	General	Peer reviewed
Australia	6	4
Belgium	3	1
Brazil	6	0
Canada	8	5
China	3	3
Korea	4	2
Spain	16	11
Finland	4	2
France	1	0
Greece	4	3
Italy	2	1
Japan	6	5
Portugal	4	1
Czech Republic	1	0
Romania	1	0
Russia	1	0
Turkey	1	0
United Kingdom	21	3
Uruguay	1	0
United States	30	20
	123	**61**

Table 1 summarizes the distribution of the various identified studies according to the countries of the companies under study. It can be seen from this table that the most researched countries in this area, or those with the greatest number of published models, are the United States (30), the United Kingdom (21) and Spain (16) with approximately 24%, 17% and 13% of the total, respectively. Regarding Peer Reviewed studies, the countries with the most studies are the United States (20), Spain (11), Canada (5) and Japan (5), which represent approximately 33%, 18%, 8% and 8% of the total, respectively.

Table 2. Number of mono sectoral and multi sectoral surveyed models

	General	Peer reviewed
Mono Sectoral	77	28
Multi Sectoral	46	33
	123	**61**

When constructing a model, this is an important decision to make, with two possible choices: a mono-sectoral sample that will improve the focus on the features of the chosen activity sector but will also be exclusively applicable to that sector; or a multi-sectoral sample, which can be more widely applied but also faces limitation related to the combination of multiple different business contexts.

Table 2 shows that 77 of the General models were developed using a mono-sectoral sample and 46 used multi-sectoral information. In the case of Peer Reviewed journals, 33 of the 46 models were multi-sectoral.

Table 3. **Number of surveyed models by type of data treatment**

	General	Peer reviewed
Matched	11	7
Paired	30	21
No treatment	82	33

Focusing on the type of data treatment, Table 3 shows that "No treatment" is the most frequent alternative, and that the most recommended techniques in the literature are the matched or paired samples.

In the first case, for each company considered "bankrupt" there will be one or more in the sample of healthy companies with similar size and characteristics, whereas in the second, there will be only one corresponding company with similar size and characteristics in the sample of healthy companies. In order to define these characteristics, several parameters are used besides activity sector, such as the totals for the balance sheet, revenues, number of employees, turnover, etc.

More specifically, in the General group, about 67% of the authors did not apply any special treatment to the sample of companies that they used. On the other hand, about 24% chose to pair their companies, with the most common characteristics used to pair the companies—apart from the industry or activity sector and, of course, the reference period—being the totals of balance sheet and turnover.

In this respect, the Peer Reviewed group presents approximately 54% of the selected models without any treatment and about 34% with a paired type sample.

Table 4. **Main descriptives of surveyed models (I)**

Peer Reviewed		Sample			
	Number of years	Number of failed	Number of non failed	Training set	Testing set
Average	9	122	1055	1153	221
Standard Deviation	5.12	215.23	1981.46	1935.89	285.27

General		Sample			
	Number of years	Number of failed	Number of non failed	Training set	Testing set
Average	8	104	647	680	191
Standard Deviation	5.30	210.89	1939.39	1898.03	277.13

Table 4 shows that in the General group, the models cover an average period of eight years of financial data, which is one less than in the Peer Reviewed group.

Regarding the distribution between "bankrupt" and not "bankrupt" companies, in the General group sample, the former accounts for about 14% of all companies studied, while the corresponding figure for the Peer Reviewed group is approximately 10%.

Regarding the testing samples, they are used in about 76% of cases in the General segment and in about 59% of Peer Reviewed studies. The size of the testing samples relative to the training sample is approximately 19% and 28% in the Peer Reviewed and General groups, respectively.

Table 5. **Main descriptives of surveyed models (II)**

Peer Reviewed	Number of indicators		Accuracy Rate		Errors		
	Studied	Final	% of "bankrupt"	% of Not "bankrupt"	Type I	Type II	Number of Functions
Average	19	6	76.40%	84.10%	23.60%	15.90%	1
Standard Deviation	28.93	6.44	0.19	0.13	0.19	0.13	0

General	Number of indicators		Accuracy Rate		Errors		
	Studied	Final	% of "bankrupt"	% of Not "bankrupt"	Type I	Type II	Number of Functions
Average	26	7	76.90%	84.00%	23.10%	16.00%	1
Standard Deviation	28.59	6.38	0.19	0.13	0.19	0.13	0.23

It can be seen in Table 5 that the studies published in Peer Reviewed journals analyse an average of 19 indicators, of which 30% of them (on average) are selected as discriminators to be used in the discriminant function. They produce an overall accuracy rate of around 80%, with the overall average error rate obviously being approximately 20%.

Regarding the General group, however, these studies analyse an average of 26 indicators, only 7 of which (on average) are selected as discriminators. It is important to highlight that the difference in the levels of correct classifications and errors with the Peer Reviewed group isinsignificant.

In both cases it is found that the studies typically present models with only one function.

6. Conclusions and opportunities for improvement

At this point, we can see that some of the limitations mentioned in section 3 have, to an extent, been considered in the literature analysed, and the authors of the models sought to address these issues. However, a number of other limitations have not yet been specifically dealt with by the majority of authors, and these include:

- **Territorial Sensitivity:** we can assume that this issue was considered by various authors since we have not identified any models with a sample containing companies from several different countries, however, no septs have been taken to identify the efficiency gains of this choice;

- **Sector Sensitivity:** about 63% of the authors have designed mono-sectoral models suggesting some concern about this issue. The remaining authors defend the use of multi-sectoral modelling built on samples that attempt to portray the economy as global. It can be clearly seen that a model that is efficient for the financial sector is unlikely to be also efficient for other activity sectors as different as mining or services.

- **Time Sensitivity:** none of the models studied applies any treatment for the temporal distance between the time of design and the application, other than recalculating the weights of each indicator. Although this technique may resolve the issue, it essentially creates a new model, albeit starting from an advanced stage of the model design process;

- **Sensitivity to bias in the sample selection:** apart from discarding companies with incomplete data for the period under study, the only treatment of the samples that we have identified was the construction, in over 76% of the cases, of test or validation samples, with no further treatment of outliers;

- **Sensitivity to the quality of information:** as indicated in section 2, the better the information used, the better the model will be. We could not identify any particular care that authors took in taking into account aspects such as the auditors' opinion (in particular regarding any constraints or limitations) or checking the information obtained for signs of accounting fraud (e.g. by applying Benford's law or looking for red flag indicators);

- **Sensitive to the assumptions of the selection:** all the analysed models naturally select the active companies as healthy. For "bankrupt" companies, they pick those that have, within the period under analysis, disappeared, requested official liquidation or used any other legal framework for assisted management and creditor protection (National Bankruptcy Act, Company Act, Chapter 10 or 11, or any equivalent legislation in the country that would apply to the company). In a few cases, the "bankrupt" companies are those whose Net Worth < 0, which is the same as saying Assets < Liabilities. It is clear the importance of legal parameters can be clearly seen in the sample segmentation. The inclusion of parameters that can separate companies differently could turn out to be beneficial.

According to Bastin (1994), the term "bankruptcy" has lost its primary meaning. It is no longer considered a definitive, virtually irreversible incident or even a shameful failure, but simply a fairly common misfortune or accident of economic life.

Although we are witnessing the ongoing trivialization of the term "bankruptcy", we should not forget that it used to be the case that a company's non-compliance with its obligations or commitments to creditors was not only regarded as a serious failure but also entailed heavy penalties.

Accordingly, the techniques presented in this paper represent a valuable contribution in order to accurately predict "bankruptcy" and thus help maintain stable economic conditions. At the same time, avenues for further research include the issues raised in section 5, which, if addressed, have the potential to improve models by making them more stable and more widely applicable.

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