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The Use of Multivariate Discriminant Analysis – The multi-sectorial approach applied to the Portuguese economy

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Abstract

Over the years, economy's cyclicality and the Disaster Myopia problem, which, according to Vasconcelos (2017), Cornand and Gimet (2012, p. 301) consists of an excessive optimism about market conditions whereby economic agents tend to underestimate risk, have repeatedly brought to the forefront the harmful effects of "bankruptcy" in varied economy sectors. With this, came a recurrent demand for better ways of anticipating "bankruptcy" or, at least, to look for contingency plans that could allow it not to spread out.

In the same way that no two persons are alike, bankruptcies also differ significantly from one another, by either causes or consequences, tending to create difficulties to prediction. This article reviews the main models of multivariate discriminant analysis when applied in the multi-sectorial scope for the prediction of corporate "bankruptcy". The focus is on the different components of bankruptcy.

We gathered 78 multi-sectoral discriminatory functions, developed or reviewed by researchers between 1968 and 2016, for various time-horizons and countries. We intend to identify, in addition to the common procedures and characteristics of these analyzes and their base samples (Peres, 2014; Peres and Antão, 2017), also their components and their stability, when applied to different sectors.

Key Words: Multivariate Discriminate Analysis, Corporate Bankruptcy, Prediction models, Forecast, Multi-sector.

JEL classification: G17, G31, G33

1. Introduction

According to classical theory, market imperfections and non-efficient allocation of resources may lead to economic regulation playing a role in minimizing bankruptcies.

According to Silva (2006) and Silva (2010), in banking, a cornerstone and engine for the economy, in 1987 (and later revised in 1998) several measures were proposed by the Basel Committee, becoming known as the *International Convergence of Capital Measurement and Capital Standards* or, more commonly, *Basel I*.

After the identification of some weaknesses in this agreement and in a later one (*Basel II*), allied to the triggering of the financial crisis (stemming from the well-known bankruptcies of the US main banks, such as the Lehman Brothers and the County Bank), it was necessary to implement new measures, creating in December of 2010 the *Basel III: A global regulatory framework for more resilient banks and banking systems*.

With the implementation of these reforms, financial institutions are expected to pursue, according to Gaspar (2014, p. 43), “a rigorous credit policy that will allow them to mitigate the risk assumed against their clients throughout the life cycle of operations”.

That was to be achieved through the *Internal Rating Based* (IRB's) introduced by *Basel II*, with the objective of determining *Probability to Default* and *Expected Loss*, the last one making possible the provisioning for the potential losses of the credit portfolios.

For these two issues, important contributions were listed from the corporate "bankruptcy" predicting methodology. From these, we highlight the work of Beaver (1966) and Altman (1968) with, respectively, the univariate and multivariate discriminant analysis, whose models would be later re-tuned both by the authors themselves and by many other researchers from different latitudes.

It should be noted that, as remarked in this article and in Peres and Antão (2017, p.110), the term "bankruptcy" and its variations is ambiguous, due to the lack of consensus in the literature as to its meaning. Definitions range from the company's inability to meet commitments, to the value of Assets being smaller than that of Liabilities. Due to that we will assign to "bankruptcy" all the commonly used meanings and the term will appear within brackets.

This article aims to provide an exhaustive survey of multi-sectoral application of multivariate discriminant analysis models, their characteristics, advantages and limitations, focusing on the indicators that compose them and the different types of results obtained when applied to different sectors of activity, types or size of enterprises.

2. Multivariate Discriminant Analysis

Historically, the statistical approach was the first one to emerge, being usually simple, easy and quick to use.

Although research on this subject began in the 1930s, the first model of univariate analysis appears with Beaver's study in 1966, although having the limitations inherent to this type of analysis.

Altman (1968, p.591) gave an example of those, 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*". In the same vein, Divsalar et al. (2011) argue that different ratios can move in opposite directions, thus producing different predictions.

The natural evolution led to the simultaneous consideration of several indicators, realized by Altman in 1968, showing a strong improvement in the forecast, thus creating the Z-Score model and, with it, the application of the Multivariate Discriminant Analysis (MDA) to the "bankruptcy" forecast.

MDA detects the group elements' attributes that distinguish them from those belonging to another group. Based on these, it is then possible to predict to which group any new element will belong.

MDA requires and assumes that the variables of the sample, commonly financial indicators, have a normal multivariate distribution, and that the company under analysis is comparable to the ones originally used in the model estimation.

Obviously, the better the information used, the better the results obtained, therefore the prediction ability can be reduced by information's quality, or, as an example, by differences in accounting treatment.

As this technique is extensively studied, it makes it easier also to see its sensitivities. As identified by Peres and Antão (2017, p.115), these are:

1- Territorial: a model designed for a specific country, area or region will potentially perform differently when applied to a geographically different sample.

2- Sectorial: each sector has specific characteristics, from the performance of its financial indicators to its operation intrinsic characteristics.

3- Temporal: it is unlikely that a model projected in the middle of the 20th century will produce the same classification performance when applied to a present sample of undertakings, even if they are from the same country, sector and with similar size and characteristics to those used to design the model.

4- To the sample selection bias: 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 "bankrupt");

5- Selection assumptions: in addition to all previous sensitivities, the model is also defined by the analyst's opinion on the financial indicators that should, or not, be included on it.

On this matter are noteworthy the works of Tinoco and Wilson (2013) and Altman, Iwanicz-Drozdowska, Laitinen and Suvas (2014).

The first ones sought to address the sensitivity stated at 3 using a sample of United Kingdom's listed undertakings, macroeconomic (consumer price index and deflated rate of treasury bonds) and market variables (belonging to groups 7 and 8 described in section 4.1, respectively), naturally limiting the model's applicability to listed undertakings, which usually represent a fringe of the entire business fabric.

The seconds, similarly, sought to analyze and combat the effect on the differences in accounting treatment and sensitivities 1 to 3, and 5, using samples with several thousand undertakings from 34 countries (31 Europeans, the United States of America, China and Colombia) and the model of Altman and Hotchkiss (1983), Z'', through the recalculation of weights, introduction of dummy variables and of other indicators such as the Standard & Poor's Country rating rank.

In this article, in addition to an overview of sensitivities 1 and 4, our focus will be mainly on the 2 and 5, as well as on the relationship that may exist between them.

3. Analyzed Models

In line with the advocated by Peres and Antão (2017, p. 118-120) seeking to explore and identify the most common and intrinsic characteristics of the models using the MDA approach, specifically with a multi-sectoral or industrial sample, we thereby identified 78 different formulations in the period of 1968-2016.

Table 1 - Surveyed models by country

Austrália	1
Belgium	5
Brazil	6
Canada	**8**
Argentina	2
Nederlands	2
Spain	**14**
Finland	3
France	5
Greece	6
Poland	3
Japan	2
Pakistan	1
Portugal	3

United Kingdom	6
Uruguay	1
United States	**10**
	78

Table 1 summarizes the distribution of the identified studies by the sample's undertakings' countries used by their authors. It is therefore identifiable that the countries with the most researchers in this field, or with more published models, with a multi-sectoral or industrial sample are Spain (14), the United States of America (10) and Canada (8), with approximately 18%, 13% and 10% of the total, respectively.

Table 2 - Number of models by the sample's type of data treatment

Matched	3
Paired	52
No Treatment	23
	78

Table 2 shows that the most frequent alternative is the paired type sample, where for each company considered as "bankrupt", correspond only one in the healthy undertakings' sample, similar in characteristics and size. In the corresponding samples (Matched) there will be one or more undertakings in the healthy sample similar in size and characteristics.

More specifically, about 29% of the authors did not apply any treatment to the sample used, where in most cases the entire population of the analyzed sectors was used, such as by Xu and Zhang (2009) or Agarwal and Taffler (2008). On the other hand, around 67% chose to match their undertakings.

Table 3 - Main characteristics of the collected models

			Sample		Accuracy Rate		Errors	
	Number of Years	Number of indicators	Number of Failed	Number of Non Failed	Failed (%)	Non Failed (%)	Type I (%)	Type II (%)
Average	9	5	109	213	83,02	81,77	16,98	18,23
Standar Deviation	5,65	1,90	164,74	504,99	10,70	17,21	10,70	17,21

Table 3 shows that the models cover an average period of nine years of financial data.

Also, regarding the samples' distribution between "bankrupt" and non-"bankrupt" entities, the first ones represent about 34% of the undertakings analyzed.

It can also be observed that the studies use in average 5 indicators, obtaining an average global rate of correct classifications of about 82%, with an overall average error rate of approximately 18%.

4. Financial Analysis, the Models' Indicators and Ratios

Ample are the characteristics that can be deduced from the indicators containing a company's accounting information, such as its financial health, performance and the perception of these by the stakeholders. According to Brealey and Myers (2010), financial analysis is generally seen as a key to reveal what is hidden in accounting information, but it is not by itself a crystal ball, rather it is a lit candle in a dark room. As Brealey et al. (2001) and Ross et al. (2002) argue, it summarizes a large amount of information helping analysts ask the right questions.

We can see only the relation between accounting items or observe it as Breia et al. (2014), interpreting them broadly as a tool for the financial department and the entities that have relations with the company (suppliers, banks, customers, investors, etc.).

The 78 models identified present a plurality of ratios or economic and financial indicators. Each model combines between 2 and 12 of these indicators to predict the financial status of the company under analysis. There are 90 different indicators, as shown in Appendix I. Generally, it is possible to divide those indicators in the following major groups:

1. Capital Structure or indebtedness: oriented mainly for the long term, shows how much debt is burdened by the company. In other words, the degree of its appeal to outside capital; are part of this group the indicators number: 23, 29, 33, 41, 43, 46, 51, 55, 56, 58, 61, 67, 72, 74 and 86;

2. Liquidity: in a general sense, it assesses the ability to meet short-term commitments; higher the mark, greater will be the company's capacity to meet its commitments in the short term. They may have some ambiguous characteristics to the users, due to the current (short-term) Assets and Liabilities being easily changed, therefore making them easily outdated. In this group are the indicators number: 1 to 3, 12, 13, 18, 20 to 22, 26, 44, 50, 63, 75, 80, 82 and 84;

3. Profitability: generally, corresponds to the relation between results obtained and means used to obtain them, and express concretely the relation between any result and the company's Sales or Capitals. Normally these are useful as complementary analysis rather than effective sources of information per se. Are members of this group the ratios: 11, 14, 30, 34, 37, 47, 59, 62, 65, 68 to 70, 76, 83 and 88 to 90;

4. Activity, operation or efficiency: seek to characterize aspects of the company's activity, such as efficiency in the use of resources or assets detained, fiscal and financial efficiency, etc. belong to this group the indicators: 4, 6, 8, 9, 15, 16, 24, 27, 28, 31, 38, 42, 49, 52, 57, 64, 66 and 71;

5. Relative weight: they are no more than the weight of an item in the patrimonial mass to which it belongs; are elements of this group the ratios: 5, 10, 17, 32, 35, 36, 39, 40, 45, 48, 73, 79, 85 and 87.

6. Dummys and dichotomous: use machine or binary language, assuming the value 1 or 0 depending on whether the entity under analysis meets or not the criteria to which they refer; the ratios 77, 78 and 81 are elements of this group.

7. Market: seek to relate the company headings to the dividends, or to it's number of shares, being proxy of the accounting performance perceived by the investors; belong to this group indicators number 53 and 54.

8. Others: facts, occurrences or relationships of items that show a correlation with the financial health of the company, the ratios 7, 19, 25 and 70 are elements of this group.

After analyzing the indicators mentioned above and the groups to which they belong, it is concluded that in the 78 identified formulations, there is a total of 312 ratios, belonging most of them mainly to the groups of indebtedness (120), activity (73), profitability (62) and liquidity (57), evidencing the authors' search for the relationship between corporate "bankruptcy" and the degradation of the indicators belonging to these groups. However, as indicated by Carvalho (2013), "the forecast of "bankruptcy" does not necessarily mean that it will happen". It should also be pointed out that the relative weight, dichotomous, others and market groups (with respectively 38, 10, 4 and 2 indicators) are smaller in relation to the previous groups, which should be mainly due to their strong variations depending on the sector of activity or the company's business type.

Table 4 - Repetition of the Observed Indicators in the Studied Models

Replays Observed	Number of indicators	
1	39	43%
2	17	19%
3	12	13%
4	4	4%
5	3	3%
6	3	3%
7	2	2%
8	1	1%
9	1	1%
11	1	1%
14	1	1%
23	1	1%
24	2	2%
25	1	1%
28	2	2%

Table 4 shows the number of times that each of the different indicators appears in the analyzed models, considering that those that were similar, equivalent or complementary were converted, it indicates a slight predominance of those with a presence in 18% or less (1 to 14 occurrences, 83 indicators) of the different models under analysis, representing 58% of the total identified. The remaining 42% refers to indicators that have between 14 and 25 occurrences, and that are present in 29 to 35% of the 78 models under study, summarizing to 6 indicators, more concretely those with the numbers 55 to 59 and 72, included in Appendix I, which belong to the leverage, profitability and activity groups, as described in section 4.1, with a predominance of the first oh those groups.

5. Empirical study

5.1 Methodology

The proposed methodology materializes itself in the study of events and it rests on six distinct phases, namely:

1. Select the relevant information.

2. Selection of indicators:

2.1 collection of the indicators that are part of the 78 models referred in section 4;

2.2 conversion and replacement of similar, equivalent or complementary indicators.

3. Acquisition of the aggregated sectoral average data by NACE - Portuguese Classification of Economic Activities, at the Bank of Portugal's Balance Sheet Central from 2010 up to 2015, inclusive.

4. Selection of NACE - Portuguese Classification of Economic Activities, collected in the previous point, that present data and undertakings in every year:

4.1. Aggregates, without separation by business size;

4.2. With separation by business dimension: micro, small, medium and large undertakings.

5. Computation of the financial indicators that compose the previously analyzed models for the average company by sector (NACE - Portuguese Classification of Economic Activities) and dimension.

6. Evaluate which indicator(s) has the highest level of stability and / or the lowest level of volatility by sector and size of firm: with results within [-1σ, $+1\sigma$] of its mean.

5.2 Sample and Data Processing

To standardize the nomenclature for the present article, we selected as proxy for the activity sector the CAE - Portuguese Classification of Economic Activities, Revision 3, which reflects the European NACE Revision 2, where the company is inserted, and therefore the information can be effectively grouped according to what INE - National Institute of Statistic and the Bank of Portugal understand as grouping of the economic activity, as shown in table 5.

Table 5 - Portuguese Classification of Economic Activities (CAE, Rev. 3 or NACE, Rev. 2)

A	Agriculture, forestry and fishing
B	Mining and quarrying
C	Manufacturing

D	Electricity, gas, steam and air conditioning supply
E	Water supply, sewerage, waste management and remediation activities
F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles
H	Transportation and storage
I	Accommodation and food service activities
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M	Professional, scientific and technical activities
N	Administrative and support service activitie
O	Public administration and defence; compulsory social security
P	Education
Q	Human health and social work activities
R	Arts, entertainment and recreation
S	Other service activities
T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
U	Activities of extraterritorial organisations and bodies

Source: adapted from INE (2007) Portuguese Classification of Economic Activities and Eurostat (2008) Statistical Classification of Economic Activities in the European Community

In the database used (the Bank of Portugal's Balance Sheet Central), the undertakings are grouped not only by NACE but also by size, in line with the recommended by Directive 2013/34/EU. In this context, the European Union (2013, p.28) recommends that the company will belong to a group if "at the balance sheet date, they do not exceed the limits of at least two of the three criteria" shown in table 6.

Table 6 - Classification of European Undertakings according to size

	Micro Undertakings	Undertakings	Medium Undertakings	Large Undertakings
Balance Sheet total (m€)	≤350	≤4 000	≤20 000	>20 000

Net Turnover (m€)	≤700	≤8 000	≤40 000	>40 000
Average number of employees (Un)	≤10	≤50	≤250	>250

Source: adapted EU (2013) Directive 2013/34/EU

After applying the segmentation criteria, recommended in sub-points 3 and 4 of the previous section, to the database of the Bank of Portugal's Balance Sheet Central, for the years 2010 to 2015 inclusive, we obtained the available data for each NACE from A to S separated by size, as well as, to combat sporadic changes in the headings, was computed the average company for the total period under analysis, which was weighted by the existing undertakings in each of the years.

This included the financial information contained in the Balance Sheet and Income Statement for the years 2010 to 2015 inclusive, as well as complementary information such as the NACE and size measures.

Compiled the information the following average business characteristics were obtained, by size:

Table 7 - Average undertakings by size from 2010 to 2015

	Micro Undertakings	Undertakings	Medium Undertakings	Large Undertakings
Net Turnover (m€)	142	1 836	11 402	119 782
EBITDA (m€)	19	353	2 173	22 446
EBIT (m€)	8	201	1 125	14 710
Net Profit (m€)	-1	81	252	8 049
Balance Sheet total (m€)	667	4 598	31 706	257 618
Equity (m€)	188	1 227	6 569	75 757
Debt (m€)	479	3 371	25 137	181 861
Number of Entities (Un)	21 492	2 362	373	65

Source: Adapted from Bank of Portugal (2015 and 2016)

To stabilize the data, the NACEs B and S were eliminated, since there are no undertakings with data available for all dimensions and periods under analysis, in addition the Bank of

Portugal's Balance Sheet Central doesn't provide data on the K, O, T and U, so we have remained with 15 NACEs, namely A, C to J, L to N, P, Q and R.

Table 7 shows the mean characteristics of these NACEs for each of the dimensions under study. It is clearly noticeable the predominance of micro and small undertakings (88% and 10% of total of undertakings, respectively), characteristic of Portugal and its business fabric composition. In addition, in all dimensions, we find an average Financial Autonomy of 26% and a tenuous EBIT margin of 10%. There is also noticeable a strong differential between EBIT and Net Income (the last one reaching negative values for micro entities). All of this makes clear the financial crisis lived within the country during the period under analysis, as well as the strong weight of taxation and the cost of debt on the corporate results (these last two together, and on average, represent around 6% of the Turnover).

5.3 Indicators Stability

Based on the information collected and previous described, we tried to compute each of the 90 indicators identified for all the NACEs and dimensions; however, 14 indicators were removed from the analysis due to the following problems:

A) Impossibility of obtaining data:

1. Considering the gathering of observations for all years and dimensions under analysis, indicators 6, 7, 25, 51, 52 and 61 were eliminated because they contained variations that would limit the analysis to 1 or 2 observations per NACE and dimension instead of the expected 6 (2010 to 2015);

2. Due to the sample containing several thousands of undertakings of different sizes, the clear majority of those unlisted, indicators 53 and 54 were eliminated by containing variables related only to listed undertakings;

B) Structural problems within their characteristics:

3. Dichotomous indicators, 77, 78 and 81 only assume the value 0 or 1 and are linked to specific NACEs lead to their analysis in others to bring little added value;

4. The indicator 19 has been eliminated by being a mathematical impossibility, since the financial variable that it uses can assume both negative and positive values and there is no Logarithm of a negative value;

5. In Portugal, in normal conditions, VAT rates may have 7 different values (3 for the Mainland, 3 for the Autonomous Regions and 1 in common for both). In the period under

review, due to the economic crisis, strong fiscal changes were made, and VAT was not an exception in both the value and the imposition of assets at such rates and therefore leading to the indicators 24 to 26 being removed.

5.4 Indicators' variation by Undertakings' Size

After treatment, there were 76 different indicators that we will try to present, the ones more stable, by company size, regardless of the NACE, which mean, the one's that have values in the range [-1σ, $+1\sigma$] in relation to its sectorial average, this being the characteristic of stability or non-dispersion. Next, and considering dimension once again, we will try to expose the NACEs that gather more indicators with respect for the identified characteristic. The results were broken down into four categories in relation to the number of indicators that weren't stable.

Table 8 – Indicators' variation by NACE, Micro Undertakings

Number of Indicators	NACE % with indicators out of the range
32	<20%
24	<30%
12	<40%
8	≥40%
76	

Table 8 shows the breakdown of the indicators due to its variations for the NACEs for the undertakings classified as micro, with 74% of them having low and medium-low dispersion (<20% and <30%) in relation to their mean. In groups with a higher level of dispersion, there are 20 indicators, the numbers of which, as shown in Annex I, are:

A) medium high (<40%): 9, 10, 37, 39, 43, 55, 60, 65, 69 and 88 to 90;

B) high (≥40%): 8, 21, 35, 48 to 50, 84 and 79.

Table 9 – Indicators' variation by NACE, Undertakings

Number of Indicators	NACE % with indicators out of the range
12	<20%
31	<30%

16	<40%
17	≥40%
76	

Table 9 shows the distribution of the indicators related to the Undertakings, where the two classes with least scattered indicators (<20% and <30%), although as in the previous company dimension they still represent most of the indicators, they revealed less accumulated value of only 57%. In relation to the classes with the highest number of indicators with dispersion, there are 33 indicators with the following numbers, as presented in Annex I:

A) medium high (<40%): 5, 23, 38, 48, 50, 56, 58, 62 to 64, 67 to 70, 72 and 88;

B) high (≥ 40%): 1, 9, 10, 13, 20, 22, 28, 34, 36, 47, 60, 66, 79, 80, 84, 85 and 90.

Table 10 – Indicators' variation by NACE, Medium Undertakings

Number of Indicators	NACE % with indicators out of the range
19	<20%
29	<30%
10	<40%
18	≥40%
76	

In relation to the undertaking dimension in table 10, the two classes that reflect the presence of a smaller number of indicators with dispersion (<20% and <30%) are also predominant, corresponding to 63% of the variables under study. Regarding the 2 classes with the highest number of indicators that do not comply with the dispersion criteria, we have 28 indicators whose numbers in relation to Annex I are as follows:

A) medium high (<40%): 1, 3, 28, 38, 50, 65, 70, 80, 82 and 85;

B) high (≥ 40%): 5, 15, 20, 27, 37, 39, 47, 49, 58, 64, 66, 69, 71, 72, 83, 84, 89 and 90.

Table 11 – Indicators' variation by NACE, Large Undertakings

Number of Indicators	NACE % with indicators out of the range
17	<20%
30	<30%

14	<40%
15	≥40%
76	

About table 11, where the distribution of indicators for large undertakings is concerned, it should be noted that also in this dimension the two classes with the lowest number of indicators where the dispersion criterion (<20% and <30%) is not respected, represent most of these, around 61%. For the remaining two classes, they have a total of 29 indicators whose Annex I numbers are as follows:

A) medium high (<40%): 10, 16, 23, 34, 55, 59, 60, 62, 63, 65, 67, 72, 83 and 88;

B) high (≥ 40%): 3, 12 to 15, 18, 20, 37, 42, 57, 64, 71, 80, 86 and 89.

In most cases, regardless of the undertakings' size under study, and within those of the various NACEs, the analyzed indicators are stable presenting values contained in the interval [-1σ, +1σ]. Of the indicators analyzed and set out in Annex I, 75% show, at least for one dimension, values outside this range. However, the most frequently classified in the last two categories indicated above are the following:

A) in 50% of the cases: 1, 3, 5, 9, 13, 15, 23, 28, 34, 38, 39, 47, 49, 55, 79, 83 and 85;

B) in 75% of cases: 10, 20, 37, 50, 60, 64, 65, 69, 72, 80, 84 and 88 to 90.

5.5 Indicators' variation by NACE

We also sought to analyze the NACEs with the lowest number of indicators out of the range described, thereby revealing a lower level of dispersion of results and consequently a true potential of the multi-sectorality of the indicators under analysis and with them, of course, their models.

Table 12 – Indicators' variation by NACE, without separation by company's size.

Number of NACE	Average % of indicators out of the range
4	<20%
7	<30%
3	<40%
1	≥40%

15

We observed, as described in table 12, as well as in the isolation by undertakings' dimension, that the great majority of the studied NACEs, more precisely 73%, presented less than 30% of the indicators as being outside the range of [-1σ,+1σ]. As for the remaining two classes, these present a total of 4 NACE, namely:

A) medium high (<40%): N, P and Q;

B) high (≥40%): R.

6. Conclusions and Improvement Opportunities

With the advance of the resources and science, more and more studies are being developed and published in all fields of knowledge. In general, we sought to bring together the most commonly identified and referenced formulations in the scientific literature as important milestones in the progression of the health and corporate "bankruptcy" research.

We came to the following conclusions:

A) New variables and formulations: we do not saw much of this occurring. Many researchers continue to create new formulations for predicting corporate "bankruptcy" based on little more than the readjustment of one or more of the previous formulations, or in other words, redefining weights of the same set of indicators using a new training sample. As shown in table 4, we identified 6 variables that are present in 29 up to 35% of the studied formulations. In addition, the 5 indicators identified in Altman's work (1968) are present all together in more than 15% of the identified formulations.

In addition, too often the demand for new variables goes beyond what is desired, as described in section 5.3 (B-2). The indicators' conversion and strong adaptation to the training sample, often without a test sample, would surely have improved the models' efficacy, however, in this case, it renders it inoperative for other samples with characteristics, even if only slightly different.

An effective use of other variables, in addition to financial indicators, is still to be identified to help counter time sensitivity, non-treatment of outliers or the potential impact of using a late classification of the company as "bankrupt".

B) Multidimensionality: In fact, we verified a great stability of the indicators used in the models under analysis. However, 51% of them were identified at the end of section 5.4 as having serious or very serious problems in at least one of the undertakings' size, regardless of the NACE.

Over the years, the economic, financial and social reality of the world has changed substantially, being a strong lead that the indicators may lose relevance and effectiveness. Therefore, the simple maintenance of these with a redefinition of weights may not always be the most appropriate of the choices.

C) Multi-sectorality: although it wasn't possible to obtain data for all the NACEs present in the Portuguese economy (as described in section 5.2), for most of the analyzed (as shown in table 12), the indicators were indeed multi-sectoral, except for the N - Administrative and support service activities, P - Education, Q - Human health and social work activities and R - Arts, entertainment and recreation.

As in the beginning of any machine's development process, the techniques presented here are still imperfect. They present flaws and encounter obstacles that research over time has been gradually supplanting, making them a valuable contribution to accuracy predict "bankruptcy" and help maintaining stable economic conditions.

The possibilities for further research include the issues raised in sections 6 and 5.3 as well as those identified by Peres and Antão (2017, p. 123), which, if addressed, may help to what Peres (2014, p. 75) and Bellovary, Giacomino and Akers (2007, p.12), indicated as *"the focus of future research should be on the use of existing bankruptcy prediction models as opposed to the development of new [...] consider[ing] how these [...] can be applied and, if necessary, refined."*

The present paper postulates, as these authors point out, the combat to the limitations and sensitivities mentioned in section 2, with the identification of success factors in the models and in the economic and financial indicators.

The future path should be traced by the search for other typologies of indicators, as realized by Altman et al. (2014), that could contribute to the improvement of the effectiveness of these models. Then, starting from the most effective ones, seeking to improve them, to maximize their forecast's effectiveness, going beyond the simple recalculation of weights, consubstantiating the investigation in the development of mechanisms, as indicated by Breia et al. (2014) and Peres and Antão (2017), "red flag indicators", that based on the accounting information seek to alert in a timely manner to weaknesses and consequent to the risk of “bankruptcy”..

7. Annex

Annex I

1	Current Assets / Current Liabilities
2	Financial Liabilities / Current Assets
3	Suppliers / Total Assets
4	EBIT / EBT
5	Cash / Total Assets
6	Average Rotation of Stocks (n–2) / Average Rotation of Stocks (n–3)
7	Standard Deviation (4 Years Net Turnover)
8	Net Profit / Added Value
9	Accounts Receivable / Net Turnover
10	Current Assets / Total Assets
11	Current Liabilities / (Net Turnover – EBIT)
12	EBT / Current Liabilities
13	Current Assets / Total Debt
14	Working Capital / Operating Expenses: (Net Turnover – EBT – Ajustments)
15	EBIT / Net Turnover
16	Staff / Added Value
17	Interest expenses / Net Turnover
18	Working Capital / Stock
19	Log(Ebit)
20	EBIT / Total Debt
21	(Permanent Capitals: Equity + Non Current Debt) / Total Assets
22	(Current Assets – Stock) / Current Liabilities
23	(Equity – Share Capital) / Total Debt
24	Supplier / (Acquisitions + VAT)

25	VAT Tax variation
26	(Stock + Net Accounts Receivable) / (Production + VAT)
27	Properties and Equipments / Added Value
28	EBT / Net Turnover
29	Working Capital / Equity
30	Current Assets – Stock – Current Liabilities / Operating Expenses: (Net Turnover – EBT – Ajustments)
31	Net Profit / Equity
32	Financial Liabilities / Total Debt
33	Equity – Non Current Assets
34	EBT / Total Debt
35	Net Total Owed Taxes/ Current Liabilities
36	Cash / Current Assets
37	Net Turnover / Total Debt
38	Net Profit / Total Assets
39	Non Current Debt / Total Debt
40	Stock / Current Assets
41	Equity / Non Current Assets
42	EBIT / (Permanent Capitals: Equity + Non Current Debt)
43	Non Current Debt / Total Assets
44	EBITDA / Current Liabilities
45	Staff / Net Turnover
46	(Equity – Share Capital) / Equity
47	(Net Profit + Ajustments) / Total Debt
48	Accounts Receivable / Total Assets
49	Net Profit / Net Turnover
50	Current Liabilities / Total Assets
51	Equity Variation / Total Assets

52	Net Turnover (n–1) / Total Assets (n–1)
53	Net Profit / Number of Shares
54	Dividends / Number of Shares
55	Working Capital / Total Assets
56	(Equity – Share Capital) / Total Assets
57	EBIT / Total Assets
58	Equity / Total Debt
59	Net Turnover / Total Assets
60	(Current Assets – Total Debt) / Total Assets
61	Equity grow rate – Total Assets grow rate
62	EBT / Total Assets
63	EBIT / Interest expenses
64	Cash–flow / Total Assets
65	Net Total Owed Taxes / Net Turnover
66	(EBT + Ajustments) / Total Assets
67	Non Current Debt / (Permanent Capitals: Equity + Non Current Debt)
68	(Net Profit + Interest expenses) / (Average of Last 2 years Total Assets)
69	Net Turnover / Working Capital
70	Net Profit / Total Debt
71	Net Profit / EBT
72	Total Debt / Total Assets
73	Cash–Flow / Net Turnover
74	(Permanent Capitals: Equity + Non Current Debt) / Total Debt
75	Stock / Working Capital
76	Net Profit / Current Liabilities
77	Activity: construction = 1; other = 0
78	Collaterals: yes = 1; No = 0
79	(Current Assets – Stock) / Total Assets

80	(Cash + Accounts Receivable) / Current Liabilities
81	Activity: distribution = 1
82	EBIT / Current Liabilities
83	Cash-Flow / Current Liabilities
84	Gross Margin /Total Assets
85	(Cash Investments + Cash)/Total Assets
86	(Equity – Net Profit) / Current Liabilities
87	Net Turnover / Cost of Goods Sold
88	Staff / Non Current Assets
89	Depreciation and Amortization / (Non Current Assets – Financial Investments)
90	(Net Profit – Current Assets + Cash) / Total Assets

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