PROBABILITY OF CORPORATE BANKRUPTCY: APPLICATION TO PORTUGUESE MANUFACTURING INDUSTRY SMES

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ABSTRACT

This paper aims to develop a model for predicting corporate bankruptcy for SMEs in the Portuguese manufacturing industry where this question remains rather unaddressed. Using profitability, activity, liquidity, leverage, and solvency ratios, it was added the size and age variables, for a group of 208 firms, including 49 bankrupt firms and 159 active firms, during the years 2011 to 2015. The logit model allowed us to estimate a model with 82.3% of predictive capacity. The most important variables identified were profitability, solvency, and size. Estimations only with the data closest to the bankruptcy date improved predictive capacity. It is evidenced that financial and non-financial variables can predict bankruptcy probability. A possible future approach would be to analyze a larger sample. Also, a larger period could be considered, allowing to test either the effects of the 2007/8 crisis or the effects of the recent economic turmoil related to Covid-19. Important for both corporate managers and investors. Conclusions may be disclosed regarding the influence that economic turmoil certainly has on corporate defaults and bankruptcies allowing its extension to other countries. The contribution of this paper is to find the best specification for a bankruptcy prediction model applied to the Portuguese manufacturing industry SMEs. This paper also contributes to the existing literature by using non-financial variables and analyzing a sector still unexplored in Portugal, albeit its conclusions can be extended to other countries.

Keywords: Bankruptcy, manufacturing industry, SMEs, logit, financial ratios.

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1. INTRODUCTION

Firms are increasingly vulnerable to the negative shocks developed in the global economy (Balcaen & Ooghe, 2006; Jayasekera, 2018; Yuan et al., 2018; Boso et al., 2019). The economic and financial crisis of 2007-2008, combined with the Portuguese debt crisis of 2011, had a major impact on the national economy, severely affecting firms and leading to a large-scale corporate bankruptcy process. The resulting adverse effects emphasize the importance of studying the firms' characteristics that could be most closely associated with bankruptcy, to take corrective strategies.

According to Instituto Nacional de Estadística (INE) (2017), in 2015 Small and Medium-Sized Enterprises (SMEs) accounted for more than 99.9% of the total number of Portuguese non-financial firms, having a great impact on the economy and employment creation. In terms of total turnover, SMEs are responsible for about 62% of the non-financial firms' turnover, thus constituting an engine for generating wealth in the national economy. According to the European Commission (2018), in 2016 SMEs in Portugal employed 2.380.449 persons corresponding to 78.1% of total employment, and representing a share of 66.6% of EU-28. SMEs present "heterogeneous" characteristics depending on the sector of activity (Antunes et al., 2016), so the analysis will focus on manufacturing industry firms', one of the most important sectors in terms of value-added and with high rates of bankruptcy in the period after the beginning of the crisis as evidenced in Pordata (2018). We exclude financial firms from the analysis because the high leverage that is normal for these firms probably does not have the same meaning as for non-financial firms, where high leverage more likely indicates distress (Fama & French, 1992). Also, we follow Lins et al. (2017) and remove financial firms from our sample due to the extensive amount of government support given to such firms during the crisis.

The weight of the manufacturing sector in the Portuguese economy is especially relevant (Pordata, 2017). Despite a significant decrease in the number of firms between 2008 and 2015, from 81.387 firms to 66.729 (accompanied by rising unemployment), it can be said that the sector is currently enjoying a recovery phase. From table 1 it is observed that i) manufacturing firms (M), in general, registered better financial performance than the total of non-financial corporations; (ii) manufacturing firms have significantly reduced their leverage and improved their profitability; iii) generally, in 2011-2012, all firms were negatively affected by the sovereign debt crisis.

Table 1: Financial Indicators For Manufacturing (M) and Non-Financial Firms (Total)

	Liquidity		**Leverage**		**Solvency**		**ROA**		**Asset turnover**	
	Total	**M**	**Total**	**M**	**Total**	**M**	**Total**	**M**	**Total**	**M**
2011	43.4%	51.4%	200.8%	178.6%	66.8%	64.1%	0.4%	1.9%	0.8	2.0
2012	42.5%	52.2%	205.7%	178.2%	67.3%	64.1%	0.0%	1.1%	0.1	1.2
2013	41.8%	52.7%	198.0%	169.3%	66.4%	62.9%	1.0%	1.8%	2.0	1.8
2014	43.8%	53.0%	205.5%	147.7%	67.3%	59.6%	0.7%	2.5%	1.3	2.6
2015	44.1%	52.7%	196.5%	137.7%	66.3%	57.9%	2.4%	5.6%	4.2	5.7

Source: Elaborated by the authors with INE data (2017).
Notes: Liquidity = Current assets/Total assets; Leverage = Total liabilities/Equity; Solvency = Total liabilities / Total assets; ROA = Net income/Total assets; Asset turnover = Turnover/Total Assets. Table 1 shows financial indicators for manufacturing firms, comparing them with all non-financial corporations between 2011 and 2015.

The study of manufacturing SMEs proposed in this paper will follow the logit methodology (Ohlson, 1980), using a regression model to classify the firms as bankrupt or active according to the available financial information. In addition to financial information, variables such as age and firm size, which have proved to be important determinants of corporate bankruptcy, will also be used (Lukason & Laitinen, 2018).

Since one prediction model would not work well in different national environments and economic periods, it is necessary to develop prediction models for specific national conditions and a particular period (Tong & Serrasqueiro, 2021). Thus, this paper contributes to the development of prediction models for Portugal during a period characterized by a severe economic downturn following the financial and European sovereign debt crises. The contribution of this paper is to find the best specification for a bankruptcy prediction model applied to the Portuguese manufacturing industry SMEs. Concerning the existing literature, such a model would be more updated and include the information about the financial deterioration suffered by many firms as a consequence of the crisis beginning in 2007-08, which had impacts that lasted until recently. Additionally, we use non-financial variables and analyze a sector still unexplored in Portugal. Since the Portuguese business environment is mainly composed of SMEs it is imperative to analyze what factors may affect their probability of failure. For the Portuguese case, most of the corporate failures (73%) are from companies in their first 20 years of the life cycle (Jardim & Pereira, 2013). It is important to study the Portuguese manufacturing sector since findings support the conclusion that some financial and economic variables do influence bankruptcy and default probability together with survival-time. This analysis is important for both corporate managers and investors and allows us to observe that it may be perfectly anticipated by corporate finance analysis theory and practice. Finally, this study contributes to the existent literature by providing evidence of a higher predictive capacity of bankruptcy considering a sample of SMEs (the higher representation of firms in Portugal).

This paper is organized into five sections. Section two reviews the literature, defining corporate bankruptcy and presenting its main causes as well as the most commonly used models for predicting it. Section three presents the sample and the methodology to be used and section four presents the estimated results, its discussion, and comparison with those obtained by previous authors. The final section presents the main conclusions and limitations of the paper.

2. LITERATURE REVIEW

2.1. Definition of Bankruptcy

"Corporate bankruptcy" is a hard term to define since it encompasses a dynamic process (Appiah, 2011). However, the financial literature proposes a wide range of possibilities, with different terms appearing in an attempt to portray the formal process that affects the firm and to categorize the economic problems involved. Altman and Hotchkiss (2006) highlight four terminologies commonly used in the financial literature to refer to firms in financial difficulties: failure, insolvency, default, and bankruptcy (Agrawal & Maheshwari, 2019).

Bankruptcy, in the view of Karels and Prakash (1987), includes negative net worth, non-payment to creditors, bond bankruptcy, inability to repay debt, overdraft bank accounts, non-payment of preferential dividends, or liquidation. In his study, Beaver (1966) defines bankruptcy as the firm's inability to pay its financial obligations at maturity and is considered bankrupt when one of the following events occurs: bankruptcy, default on a bond, or non-payment of preferential dividends. For Deakin (1972), firms that have experienced bankruptcy, insolvency, or have been liquidated to the benefit of creditors are bankrupt. Blum (1974) views bankruptcy as the inability of the debtor to pay its obligations as they mature, by entering bankruptcy proceedings or by signing renegotiation and debt reduction agreements. For Zeitun et al. (2007) the firm is assumed to be in default when the profit or cash flow of the current year is negative or less than the total of the debts, or whenever the sum of the profit and the expected value of the capital negative. For Hazak and Männasoo (2007) bankruptcy refers to the situation in which the debtor is legally declared unable to pay its creditors.

Altman (1968), Ohlson (1980), Zavgren (1985), Platt and Platt (1990), and Charitou et al. (2004) define their sample of bankrupt firms in legal terms, that is, firms that have been legally declared "bankrupt". For Laitinen (1994) bankruptcy corresponds to the inability of the firm to meet its obligations as they mature, similar to the technical insolvency of Altman and Hotchkiss (2006). In more recent studies such as Jacobson et al. (2013), the firm is assumed bankrupt when declared legally bankrupt, suspends payments, is under reconstruction procedure, or has no assets to settle its debt. On the other hand, Situm (2015) presents two criteria to consider the firms as bankrupt, one from the perspective of the Austrian legislation and another one when they have registered negative results for two consecutive years. The definition presented by Pacheco (2015, 2019) represents the cessation of firm activity and incorporates voluntary liquidation and dissolution. This wide range of interpretations of the dependent variable is pointed out by Ohlson (1980) as a problem because there is no consensus about what "bankruptcy" is, varying significantly between authors.

Another object of study in the subject of business bankruptcy focuses on the analysis of firms in financial distress. Platt and Platt (2002) refer that this is a little-explored theme given the difficulty to objectively define the moment when the firm goes into difficulties. According to McKee (2003), the inability to compete successfully in the market and/or to generate liquid assets precedes the situation of financial difficulties, which is the last phase of the firm's decline and precedes more events such as bankruptcy or liquidation, and therefore emphasizes the importance of identifying the concept as a way of preventing financial problems. According to McKee (2003), the firm may survive for several years in financial difficulties, either because they are not very severe or because they hold additional financing capacity and the management must take concrete measures of revitalization. Tian and Yu (2017) use as an indicator of financial difficulties the omission or reduction of dividends. Whitaker (1999) defines financial distress as cash flow less than current maturities of long-term debt. Another definition is presented by Nanayakkara and Azeez (2015), who consider the firm in financial difficulties when it registers losses and/or negative cash flows for three or more consecutive years. For Bartual et al. (2013) firms with net negative or non-performing wealth are in financial distress.

Thus, according to Balcaen and Ooghe (2006), the use of the classification of financial distress represents a clear disadvantage that is the absence of a concrete definition and the possibility of arbitrariness between several perspectives. On the other hand, bankruptcy (from a legal point of view), even though it presents inherent differences in the legislation of each country (Hazak & Männasoo, 2007), allows an objective classification of the sample and the date of change of status of the legal situation (Balcaen & Ooghe, 2006; Charitou et al., 2004). However, according to Balcaen and Ooghe (2006), there is also a problem in the use of the legal concept related to the concrete moment of bankruptcy, since the legal moment is different from the real moment.

2.2. Causes of Corporate Bankruptcy

The process of corporate bankruptcy is usually slow and results from internal and external factors (and both), being the cause of the lack of liquidity (Altman & Hotchkiss, 2006). There is no clear understanding of the factors that contribute to corporate performance deterioration and consequently to bankruptcy (Lukason, 2013), as each study addresses the factors identified in its sample. Among the causes related to financial problems, can be highlighted the loss and/or inability to raise capital and high indebtedness (Levratto, 2013), lack of liquidity and insufficient information and accounting control (lack of accounting background, cash flows analysis, or firm financial records) (Arasti, 2011; Switzer et al., 2018).

For Jahur and Quadir (2012) the lack of access to sources of credit as a consequence of high-interest rates is also a cause of distress, to which Kenney et al. (2016) add the inability to finance inventory investment. Another problem arises when firms are not established with the necessary capital (capital inadequacy) to the sustainable evolution of their activity, which implies that they are in constant effort from the time of their birth and that they give in when market conditions harden (Jahur & Quadir, 2012).

According to Altman and Hotchkiss (2006), can also be considered cause of bankruptcy: the deregulation of key industries that allows more entrants and an increase in competition, throwing the least efficient ones out of the market; increasing international competition; industry overcapacity; and the high rates of firm formation registered in some periods with the prospect of future sector growth. Levratto (2013) points out reasons related to the increase of the general costs of carrying out the firm's activity and the legal disputes with creditors. He also adds internal firm issues related to poor location or loss of customers (reduction of sales is also referred by Kenney et al. (2016)), calamities and natural disasters, or fraud and theft.

Finally, it should be noted that the age and size of the firm also play an important role in the risk of bankruptcy likelihood. When entering the market, firms need to establish relationships with their stakeholders by starting their activity at a disadvantage compared to competitors already in place, placing younger firms in a more vulnerable market position (Ooghe & De Prijcker, 2008). Altman (1968) was perhaps one of the first authors to evaluate a ratio that expresses firms' age-related information, using the ratio (Retained Earnings / Total Asset) as an indicator for the age of the firm, as younger firms will have lower ratios because they do not have had time to increase their accumulated profits. According to Situm (2014), younger firms are unaware of their profitability potential, and only with accumulated experience will they realize if they have the right structures to stay in or out of the market. Altman et al. (2017) reaffirm the hypothesis that very young firms present greater risks, which is in line with that of Levratto (2013), who states that the risk of bankruptcy initially increases with age until it reaches a peak and then decreases as firms grow old.

Size is another factor that affects firms' chances of survival (Beaver, 2005; Kenney et al., 2016). According to Levratto (2013), the literature agrees with the fact that the as smaller the firm size the greater the chance of default, because smaller firms do not have the financial capacity or support of creditors to overcome more aggressive economic periods and also because they cannot capture the most competent human resources, since they do not offer the same possibility of progression or personal fulfillment as the bigger organizations.

2.3. Bankruptcy Prediction Models

The prediction of corporate bankruptcy study dates back to the 1930s when were published the first studies of financial ratios analysis as indicators of bankruptcy. This subject was, however, not very significant until the mid-1960s, becoming since then one of the main research topics in business finance (Balcaen & Ooghe, 2006; Dong et al., 2018; du Jardin et al., 2019; García et al., 2019).

Bankruptcy forecasting models can be grouped into two broad categories (Ooghe et al., 2009): market models and fundamental models. Market models introduce market information, such as stock prices. Fundamental models use accounting models, macroeconomic models, and rating models. The accounting models have a high preponderance regarding the forecast and bankruptcy probability. This methodology is developed based on accounting information, which allows the computation of financial ratios that indicate the firm's situation (Agarwal & Taffler, 2008). Although it is possible to innovate about the ratios used in this type of study since the explanatory capacity of the ratios varies over time depending on the factors that precipitated bankruptcy, in general, the indicators focus on liquidity, profitability, or leverage (Tian & Yu, 2017).

The study of accounting models is inseparable from the work done by Beaver (1966), Altman (1968), or Ohlson (1980). Beaver's (1966) work is considered the propeller of modern studies concerning business bankruptcy. In his study, through the analysis of 30 ratios calculated with firms' balance sheet information, it was verified the capacity that each indicator, individually, had in the corporate bankruptcy prediction. The author left open the need to carry out a multivariate analysis that allowed estimating a model contemplating the information of several ratios in the same prediction.

In response to the need raised by Beaver (1966), Altman (1968) developed the Multivariate Discriminant Analysis (MDA) as a statistical method used to classify an observation into one of the groups established a priori according to the individual characteristics of the observations, thus allowing to classify firms as bankrupt or active. This methodology was applied to a total of 66 firms using more than 20 financial ratios, allowing the definition of a discriminant function according to which firms that obtained scores between 1.81 and 2.67 were considered bankrupt. The model accurately classified corporate bankruptcies in 94% of the cases and classified 95% of the sample according to their groups. According to Altman (1968), this made the model very effective in predicting bankruptcy for up to two years before the firm declared bankruptcy, a prediction that declines as the time horizon is extended.

This method was widely disseminated for bankruptcy forecast and authors such as Deakin (1972), Blum (1974), Altman et al. (1977), Nanayakkara and Azeez (2015), and Paolone and Kesgin (2016), replicated the initial model, adapting it to the realities of each country, characteristics of the sector or introducing new variables. In a recent comprehensive study, Altman et al. (2017) evidence that the general Z-score model works reasonably well in a set of 34 countries (the prediction accuracy is approximately 0.75), and classification accuracy can be improved further (above 0.90) by using country-specific estimation that incorporates additional variables.

The logit model adapted by Ohlson (1980) to predict the likelihood of corporate bankruptcy, overcame some of the limitations of MDA (Singh & Mishra, 2016). The logit model applied to bankruptcy forecasting is calculated through a set of accounting ratios that allow a firm to measure its probability of bankruptcy by estimating a maximum likelihood model. According to Pacheco (2015), the logit methodology adapts well to the characterization of firms' bankruptcy, since the dependent variable is binary. The result is a score between zero and one that represents the probability of the firm being bankrupt or not, and finally, the estimated coefficients allow an individual interpretation to know which ratios have the greatest influence on the forecast.

Ohlson (1980) applied this method to a sample of 105 bankrupt firms and 2058 active for the period from 1970 to 1976, using nine explanatory variables, which allowed an overall score of 96%. In his study, it was also possible to verify that the variable used to measure the firm size had high capacity in the bankruptcy forecast and that estimation by the MDA reached results inferior to those obtained by the logit model. Afterward, some papers were developed based on the logit model developed by Ohlson (1980), namely Zavgren (1985), Platt and Platt (1990), Kim and Gu (2006), Zeitun et al. (2007), Bonfim (2009), Bartual et al. (2013) and Tong and Serrasqueiro (2021). Kovacova et al. (2018) validate its use and Jones et al. (2017) evaluate alternative statistical frameworks.

Zeitun et al. (2007) estimated a model that correctly identified 90% of bankrupt firms and 93% of active firms, generating an overall capacity of 93.3%, a result that according to the authors reveals a comparatively high bankruptcy prediction capacity when compared to other studies. Bonfim (2009) studied the determinants of corporate credit default, taking simultaneously into account firm-specific data as well as macroeconomic information. She used a sample of more than 30.000 Portuguese firms for the period comprised between 1996 and 2002. The results confirmed the hypothesis that in periods of economic growth, credit increases and, there may be some tendency to excessive risk-taking. Bartual et al. (2013) applied the logit methodology and obtained a model with an accuracy of 88,1%, and Kim and Gu (2006), in their study of the US hotel sector, succeeded in obtaining a model with a bankruptcy prediction capability of 91 % and 84% one and two years in advance, respectively. Recently, in a study for Portuguese high and medium-high technology SMEs, Tong and Serrasqueiro (2021) evidenced that profitability is the most significant indicator of business failure and financial distress. Also, the authors evidenced that indicators related to debt and liquidity were also important in predicting business failure, but the accurate rate of prediction of business failure significantly decreases with time.

Authors such as Jones et al. (2017) tested the explanatory capacity of logit and MDA concluding for the greater explanatory capacity of the conditional probability model. Also, considering the limitation of MDA, Altman and Sabato (2007), in their study on SMEs applied to the North American market, found evidence that the logistic models had a greater capacity to discriminate between bankrupt and active firms than MDA when the same variables are used as regressors. The results are in line with the ones observed by Araghi and Makvandi (2013), 81% of predictive capacity in the logit versus 70% in the MDA. Several authors argue that alternative models – Principal components analysis, neural networks models, etc. – are better since they are not dependent on assumptions about the data (e.g., Bărbuță-Mișu & Madaleno, 2020; Abidin et al., 2021). Nevertheless, the first bankruptcy models are still widely applied and provide important information. For instance, in a review of 89 studies on the prediction of bankruptcy risk, published between 1968 and 2003 and encompassing ten countries, Aziz and Dar (2006) found that the multi-variable models (Z-Score) and logit were the most popular. So, following this line of research, the present paper uses the traditional logistic regression model,

3. DATA, METHODOLOGY, AND VARIABLES

3.1. Data

The analyzed sample in this study is composed of financial data collected from the SABI database. Our sample contains SMEs from the Portuguese manufacturing industry classified according to the Classification of Economic Activity (CAE), divisions C-10 to C-33. We collected data related to 61,364 firms, of which only those that fitted in the category of SMEs were selected. The period 2011-2015 was chosen for three main reasons: first, to increase the quality of the data set, the period couldn't encompass a large number of past years, due to gaps in the data; secondly, a smaller number of years would unlikely provide the necessary information about bankruptcy prediction; finally, a data set with a larger number of years would certainly be affected by the crisis starting in 2007/8 and its serious and lasting effects on the economy. Several filters were applied: i) only firms with complete financial information for the period 2011-2015; ii) only firms with one of the following legal form: *Sociedade Unipessoal por Quotas*; *Sociedade por Quotas*; or *Sociedade Anónima*; iii) only firms that entered into insolvency during the year 2016. This set of filters allowed to define a total sample of 49 SMEs considered as "bankrupt".

To use a comparison sample, some filters were applied to find a set of active firms with similar characteristics to those of bankrupt firms to guarantee the homogeneity of the model. The coupling of the sample and the definition of the active firms to be studied was done according to Zavgren (1985), having been arbitrarily chosen from the same activity sector and holding similar total asset values in the first year of data (2011). To eliminate the observations with extreme values, 2.5% and 97.5% percentiles were defined for all explanatory variables. The firms that were defined as outliers were removed from the sample, which allowed to obtain a final sample composed of 208 firms, of which 49 were bankrupt and 159 were active.

A summary of the sample is presented in Table 2, where it can be observed that active firms present much more favorable indicators than those of firms that eventually failed in 2016. The analysis of the information from 2011-2015 for the total firms, and also disaggregated into active and bankrupt firms, shows that average turnover is higher for active firms. Based on the analysis of the liquidity indicator, both groups of firms have very similar values. In terms of leverage, the average value of the sample is 246.64%, which is also higher than that shown in Table 1. Regarding the solvency indicator, the average value of the ratio is extremely inflated by the results obtained by the bankrupt firms, since for active firms this ratio is broadly on average with the sector.

Regarding ROA, it is possible to verify that, on average, the sample presents negative values (-4.24%), being this value strongly influenced by the results obtained by the bankrupt firms. The asset turnover is very similar for both firms, but is higher for the active firms, generating an average value very similar to that obtained for the total manufacturing firms (see Table 1). Finally, it should be noted that the size of the active firms is lower, as is the number of employees.

Analyzing Table 2, it is possible to verify a continued deterioration in the financial ratios and turnover of bankrupt firms. Firms that ended up failing began with average leverage values around 200%, but the deterioration of the ratio was quite evident when the firms were bankrupt, as in 2013 the ratio assumed the value of 1801.51%, whereas in 2015 the value of the ratio is substantially reduced by the deterioration of the firm's financial situation.

Table 2: Financial and Economic Indicators of the Sample (Average Values)

	Total sample	**Bankrupt**				**Active**			
		Total	**2011**	**2013**	**2015**	**Total**	**2011**	**2013**	**2015**
Turnover (€)	1110154.6	867870.3	977310.4	933126.0	699094.1	1185293.3	803588.9	1162133.3	1579560.6
Liquidity (%)	76.94	77.80	78.71	80.78	73.74	77.70	75.02	77.74	76.42
Leverage (%)	246.64	356.58	206.22	1801.51	-418.41	212.54	264.06	400.49	0.07
Solvency (%)	89.15	142.25	93.65	107.86	278.39	72.68	73.47	73.04	69.67
ROA (%)	-4.24	-27.43	-3.43	-6.00	-1.00	2.95	0.25	4.33	5.33
Asset turnover	1.72	1.50	1.46	1.38	1.98	1.78	1.88	1.73	1.77
Size	12.5	12.9	12.9	13.0	12.6	12.4	12.04	12.5	12.8
Employees (nº)	17	25	25	25	24	14	12	13	17

Source: Elaborated by the authors.
Notes: Liquidity = Current assets/Total assets; Leverage = Total liabilities/Equity; Solvency = Total liabilities/Total assets; ROA = Net income / Total assets; Asset Turnover = Turnover/Total Assets; Size = Logarithm of total assets. See table 3 for more details regarding the variables.

In short, albeit the differences were not statistically tested, it turns out that average bankrupt firms tend to present a much more weakened financial structure when compared with firms that remain active, with bankruptcy seeming to be an unavoidable consequence. It is possible therefore to state that although there are some divergences between our sample and the sector real scenario, it will be possible to find satisfactory and reliable results for the studied firms.

3.2. Methodology and Variable Selection

The analysis of selected data will be carried out with the logit methodology, which for the reasons highlighted above and due to the specific characteristics of the sample, was considered to be the most appropriate (Costa, 2014; Pacheco, 2015; Kovacova et al., 2018; Pacheco, 2019).

The logit model is a conditional probability model and is represented by the following function:

$$\Pr(Y_i = 1) = F(\boldsymbol{X_i\beta}) = \frac{1}{\mathbf{1}+e^{-X_i\beta}} \tag{1}$$

The dependent variable is a binary value, where “1” is assigned to bankrupt firms and “0” to active firms. An extensive analysis was carried out for the dependent variables which correspond to the most used ratios in the corporate bankruptcy prediction, being the ratios most often classified as statistically significant for predicting bankruptcy or that have been used more frequently (whereas or not statistically significant) and are presented in Table 3, where it was added a variable related to firm size [log (TA)] and the variable age, measured by the number of years that the firm has been active until the studied year.

Some of the variables present similar measures and as such, it is necessary to verify the possibility of correlation between them. Analyzing the correlation matrix (Table 4) it is possible to verify that the EBITTA and CFTA, EBITTA and NITA, and NITA and CFTA ratios are strongly correlated and therefore should not be included simultaneously in the same regression. This correlation was expected since all of those ratios belong to the same category (profitability) and should therefore be individually included in the model to avoid multicollinearity. The TDTA variable also shows a very strong correlation with the three liquidity ratios, so there should be some caution in their joint use. The other variables present correlation coefficients with smaller absolute values, thus indicating no serious collinearity problems.

Table 3: Ratios Used by Several Authors and Reference to Papers in Which They Were Considered Important in Predicting Corporate Bankruptcy

Ratio	Category	(1) Significant in (2) Examined but not significant or not incorporated in the final model	Expected sign
TDTA: $\frac{Total\ liabilities}{Total\ Assets}$	Solvency	(1) Beaver (1966); Ohlson (1980); Zmijewski (1984); Platt and Platt (1990); Kim and Gu (2006); Pervan et al. (2011); Lakshan and Wijekoon (2013) (2) Taffler (1982); Altman and Sabato (2007); Zeytinoglu and Akarim (2013); Nanayakkara and Azeez (2015)	+
WCTA: $\frac{Working\ Capital}{Total\ Assets}$	Liquidity	(1) Beaver (1966); Altman (1968); Ohlson (1980); Lakshan and Wijekoon (2013); Coats and Fant (1993); Almansour (2015); Paolone and Kesgin (2016) (2) Altman et al. (1977); Altman and Sabato (2007); Pervan et al. (2011); Nanayakkara and Azeez (2015)	-
CACL: $\frac{Current\ assets}{Current\ liabilities}$	Liquidity	(1) Beaver (1966); Altman et al. (1977); Zmijewski (1984); Almansour (2015); Tong and Serrasqueiro (2021) (2) Platt and Platt (1990); Kim and Gu (2006); Pervan et al. (2011); Lakshan and Wijekoon (2013)	-
CATA: $\frac{Current\ assets}{Total\ Assets}$	Liquidity	(1) Pervan et al. (2011) (2) Beaver (1966); Taffler (1982); Platt and Platt (1990)	-
NITA: $\frac{Net\ income}{Total\ Assets}$	Profitability	(1) Beaver (1966); Ohlson (1980); Zmijewski (1984) (2) Platt and Platt (1990); Kim and Gu (2006); Altman and Sabato (2007); Almansour (2015)	-
CFTD: $\frac{Cash\ Flow}{Total\ liabilities}$	Profitability	(1) Beaver (1966); Nanayakkara and Azeez (2015) (2) Taffler (1982); Platt and Platt (1990); Lakshan and Wijekoon (2013)	-
EBITTA: $\frac{EBIT}{Total\ Assets}$	Profitability	(1) Altman (1968); Altman et al. (1977); Taffler (1982); Coats and Fant (1993); Pervan et al. (2011); Paolone and Kesgin (2016) (2) Platt and Platt (1990); Kim and Gu (2006); Lakshan and Wijekoon (2013); Nanayakkara and Azeez (2015); Pacheco (2015)	-
CFTA: $\frac{Cash\ flow}{Total\ Assets}$	Profitability	(1) Lakshan and Wijekoon (2013) (2) Beaver (1966); Taffler (1982); Platt and Platt (1990); Nanayakkara and Azeez (2015)	-
SalesTA: $\frac{Turnover}{Total\ Assets}$	Activity	(1) Altman (1968); Coats and Fant (1993); Zeytinoglu and Akarim (2013); Almansour (2015); Paolone and Kesgin (2016)	-

		(2) Altman et al. (1977); Platt and Platt (1990); Kim and Gu (2006); Altman and Sabato (2007); Pervan et al. (2011); Lakshan and Wijekoon (2013)	
TDE: $\frac{Total\ liabilities}{Equity}$	Leverage	(1) Zavgren (1985); Zeytinoglu and Akarim (2013) (2) Taffler (1982); Lakshan and Wijekoon (2013); Almansour (2015)	+

Source: Elaborated by the authors.

Table 4: Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12
TDTA	1.00											
WCTA	-0.33	1.00										
CACL	-0.15	0.24	1.00									
NITA	-0.90	0.23	0.05	1.00								
CFTD	-0.27	0.06	0.21	0.28	1.00							
EBITTA	-0.90	0.24	0.06	1.00	0.30	1.00						
SalesTA	0.49	-0.22	-0.11	-0.46	0.01	-0.45	1.00					
CFTA	-0.90	0.23	0.05	1.00	0.29	1.00	-0.45	1.00				
TDE	-0.01	0.01	-0.04	0.01	-0.01	0.01	0.00	0.01	1.00			
CATA	0.01	0.28	0.21	0.00	0.05	-0.02	0.04	-0.02	0.08	1.00		
log(TA)	-0.12	0.01	-0.25	0.09	-0.04	0.09	-0.24	0.08	0.02	-0.13	1.00	
Age	0.03	0.06	-0.03	-0.05	-0.10	-0.06	-0.06	-0.06	0.01	-0.06	0.28	1.00

Source: Elaborated by the authors. See Table 3 for the definition of the variables.

4. EMPIRICAL RESULTS AND DISCUSSION

In this section, we present the results obtained through the application of the logit methodology to the data. Table 5 presents the models' results. The model I includes all explanatory variables and model II includes only those that have proved to be significant. Analyzing the results of model I, it is possible to verify that the R^2 McFadden, measuring the adjustment quality, reaches the value of 27.1%. Regarding the obtained coefficients, it is possible to verify that variables WCTA, CFTA, and TDE are not statistically significant for predicting corporate bankruptcy. When a model is estimated without the introduction of these variables (model II) it is possible to verify that the predictive capacity decreases slightly, although the adjusted R^2 shows a better model performance.

In Model II it is possible to verify that TDTA is statistically significant and has the expected positive impact on the bankruptcy likelihood. These results contradict those obtained for example by Ohlson (1980) or Platt and Platt (1990). The CACL and CFTD ratios are statistically significant and show the expected effect on the bankruptcy probability for the Portuguese manufacturing industry SMEs (an effect recently confirmed by Tong and Serrasqueiro, 2021). The CACL ratio has a negative coefficient similar to the one presented by Almansour (2015). The SalesTA measure is statistically significant and its impact is similar to that obtained by authors such as Almansour

(2015) in the external context and by Oliveira (2014) in studies for Portuguese firms. The CATA ratio is marginally significant and shows the expected positive coefficient, similar to Pervan et al. (2011). Finally, size and age variables are both important in explaining the firms' probability of failure.

Table 5: Estimated Models for The Five Years Before Bankruptcy

Model I				Model II			
	Coefficient	*z*			Coefficient	*z*	
constant	-565.229	-5.774	***	constant	-551,426	-5,746	***
TDTA	148.301	4.950	***	TDTA	142,221	5,680	***
WCTA	0.43667	1.158					
CACL	-0.26902	-2.975	***	CACL	-0,25333	-2,977	***
CFTD	-274.333	-2.280	**	CFTD	-337,149	-5,809	***
SalesTA	-0.51126	-4.308	***	SalesTA	-0,55073	-4,766	***
CFTA	-0.82532	-0.555					
TDE	0.00071	0.363					
CATA	0.93657	1.892	*	CATA	118,560	2,726	***
logTA	0.27096	4.282	***	logTA	0,26147	4,155	***
Age	0.01537	1.814	*	Age	0,01814	2,213	**
R^2 McFadden	27.1%				26.9%		
R^2 adjusted	25.2%				25.5%		
Predictive Ability	83.0%				82.3%		

Source: Elaborated by the authors.
Notes: ***, **, * - Statistically significant at 1%; 5% and 10%, respectively. See table 3 for variables definition.

Size is an extremely useful indicator in predicting corporate bankruptcy in this sample (it is statistically significant at 1%) as it had been in Ohlson (1980) and is also in line with studies of Beaver (2005) and Nanayakkara and Azeez (2015) who had referred to it as one of the main variables in explaining corporate bankruptcy. Regarding age, and according to the theory, it is expected to negatively influence the probability of the firm to fail, but in this study the sign is contrary to the expected, contradicting the theory that firms with more years in operation have more accumulated experience as well as capital to deal with the most difficult situations and thus to reduce their probability of bankruptcy.

Model II presents the best classification in the adjustment quality measure and allows to achieve a high percentage of correctly predicted cases, obtaining an accuracy rate in the separation of the firms by groups of bankrupt and non-bankrupt of 82.3%. With the results obtained by model II, it is possible to write the following logistic function that best describes the bankruptcy prediction taking into account the used ratios (equation 2).

$$prob_i = \frac{1}{1+e^{-(-551{,}43+142{,}22\,TDTA-0{,}25\,CACL-337{,}15\,CFTD-0{,}55\,SalesTA+118{,}56\,CATA+0{,}26\log TA+0{,}02Age)}} \quad (2)$$

To quantitatively evaluate the impact of each of the ratios on the bankruptcy probability, an application of the logit odds ratio was performed, allowing to verify the probability of an event occurring relative to the probability of the non-event. This measure provides additional information since it measures the impact of each variable on the corporate bankruptcy likelihood. The estimation of the odds is done by calculating the exponential value of the estimated coefficient by the logit model (Kovacova et al., 2018). To interpret the estimated values for the bankruptcy probability, to each of the estimated coefficients must be subtracted (-1) and performed the percentage multiplication (Buis, 2012). Thus, by interpreting the results in Table 6 it is possible to state that the bankruptcy probability increases by 314.6% when the TDTA coefficient increases by one unit. On the other hand, when SalesTA increases one unit, the bankruptcy probability decreases by 42.3%.

Table 6: Logit Odds Ratio for Model II

Variable	const	TDTA	CACL	CFTD	SalesTA	CATA	logTA	Age
Coefficient	0,004	4,146	0,776	0,034	0,577	3,273	1,299	1,018

Source: Elaborated by the authors.
Note: See table 3 for variables definition.

Since Model II was considered the best in terms of predictive capacity, we estimated three more models presented in Table 7 in which the model is replicated to time-lagged horizons to verify its predictive capacity for one, three, and five years before the bankruptcy.

From the analysis of Table 7, it is possible to verify that the predictive capacity of the model when applied to data referring to the last year before bankruptcy is 90.4%, much higher than that obtained with the estimation with data referring to five years before bankruptcy (78.8%). Regarding the quality of the adjustment, it is also observable that it is higher for the estimated model with data from the last year before bankruptcy and decreases when are considered previous years. The variation in the adjustment quality and predictability resulting from the use of more current or older information is perfectly understandable: as firms approach the date of bankruptcy, their financial information deteriorates, transferring to the calculated financial ratios information that leads to the awareness that the firm will default and possibly end its operations.

Table 7: Predicted at 1, 3 and 5 years Before Bankruptcy with the Application of Model II

	1 year before bankruptcy (2015)			**3 years before bankruptcy (2013)**			**5 years before bankruptcy (2011)**		
	Coef.	***z***		**Coef.**	***z***		**Coef.**	***z***	
const	-3.88176	-1.409		-5,57872	-2,534	**	-7,22990	-3,447	***
TDTA	1.85521	2.537	**	1,39430	2,550	**	1,02304	1,979	**
CACL	-0.79853	-1.722	*	-0,24709	-1,377		-0,18397	-1,088	
CFTD	-5.79414	-2.620	***	-2,86265	-2,949	***	-1,22940	-1,136	
SalesTA	-0.67009	-2.394	**	-0,58794	-1,825	*	-0,41138	-1,723	*
CATA	1.86141	-1.684	*	1,55061	1,401		1,76494	1,811	*
logTA	0.11150	0.589		0,24632	1,751	*	0,37859	2,809	***
Age	0.02150	0.942		0,02206	1,218		0,01600	0,897	
R^2 McFadden	50.7%			22.8%			15.6%		
R^2 adjusted	43.7%			15.8%			8.6%		
Predictive Ability	90.4%			81.8%			78.8%		

Source: Elaborated by the authors.

Notes: ***, **, * - Statistically significant at 1%; 5% and 10%, respectively. See table 3 for variables definition.

Some of the highlights of this analysis focus on the signs and the significance of the estimated coefficients. In the one-year model only the variables TDTA, CACL, CFTD, SalesTA, and CATA are statistically significant. From the signs related to these variables that have been highlighted, it is important to mention that except for CATA, all signs are following what was expected. The inconsistency of CATA could be due to the presence of accumulated data for different periods before bankruptcy (Switzer et al., 2018).

In the estimated model with three-year data, the results are quite similar, except for the CACL and CATA variables, which are no longer significant, turning the size variable to be relevant, which is in line with the papers applied to Portugal (Costa, 2014; Oliveira, 2014; Pacheco, 2019). For 2011 data, the estimation only found four explanatory variables as statistically significant (TDTA, SalesTA, CATA, and size). The variables explaining the bankruptcy of SMEs in the manufacturing industry five years in advance show signs that are in line with those that have been presented throughout the rest of the paper, so there is a sequence that is stable over the sample.

Returning to the Model II results, presented in Table 5, it should be noted that the 82.3% value for the predictive capacity is relatively high about what has already been obtained in the relevant literature. Pacheco (2015), analyzing SMEs in the Portuguese hotel industry, estimated a model that correctly classified 69.7% of the firms in the sample. On the other hand, Lopes (2014) analyzing 490 Portuguese SMEs, representatives of several sectors of activity, between 2005 and 2008 obtained a model with a global hit capacity of 80.3%. The results obtained by Pacheco (2015) were classified by the author as not very robust and for Lopes (2014) the results obtained were inferior to those obtained at the international level. Pacheco (2015) points out as a cause of the poor robustness of the results the poor quality of the financial data reported by the national firms, which prevents a concrete analysis and with more significant results. Related to this issue, Serrano-Cinca et al. (2019) use a set of financial ratios especially designed to detect accounting anomalies as bankruptcy predictors, as do Dong et al. (2018).

One of the studies carried out in Portugal that took a similar approach and analyzed the probability of bankruptcy with one of the time horizons of one year was Costa (2014). In his work, with firms from the construction sector, he was able to obtain a function that correctly characterized 75.7% of the firms in his sample a year before bankruptcy. Like Pacheco (2015), it is possible to affirm that the lower explanatory capacity of the model is a result of the weak financial information transmitted by the firms, which makes it impossible to analyze them more carefully and obtain more robust results.

Thus, it is possible to conclude that, although in some models, explanatory variables with no statistical significance are included in the explanation of corporate bankruptcy, and there are signs that are contrary to what was predicted a priori for the expected impact of these variables, corporate bankruptcy is predictable up to 5 years before the bankruptcy with a capacity of adjustment of 82.3% being the variables with more relevance TDTA and SalesTA, both having the expected signal and registered the greatest impacts in predicting the corporate bankruptcy probability. When analyzing the results of the last year before bankruptcy, the probability of success rises to 90.4%, which even in the case of analysis at a later stage still allows to define the classification of the firm with greater rigor and still gives some time to take corrective action to reverse the position or minimize the effects of bankruptcy when recovery is no longer possible.

5. CONCLUSION

This paper has an exploratory nature since the determination of the variables that explain bankruptcy remains an empirical question rather unaddressed in the Portuguese context. To develop the present analysis, 208 manufacturing SMEs firms were selected, of which 49 were bankrupt and 159 remained in business. Bankrupt firms were defined as having started insolvency or liquidation proceedings in the year 2016 and were analyzed in the five years before the bankruptcy (2011 to 2015). For this period, financial ratios were calculated with the financial information available, and two variables related to firm size and age were added.

The results obtained allowed us to demonstrate the applicability of the logit methodology in the estimation of the corporate bankruptcy probability. They also revealed that some of the chosen ratios display a high explanatory capacity to predict bankruptcy, as had already been the case in previous studies, although some of the ratios appear to have an opposite impact than would be expected. The variables that are constantly statistically significant in the various models that have been estimated and have the greatest impact on the probability of bankruptcy are the solvency ratios (TDTA) and activity (SalesTA). Most of the explanatory variables presented coefficients with the signal equal to the expected one, except for the liquidity variable (CATA) and the non-financial variables Size and Age. The CACL (liquidity) and CFTD (profitability) ratios are also good indicators in explaining the bankruptcy probability for SMEs in the manufacturing industry, appearing with the expected signs. It should be noted that the other measures of profitability (EBITTA, CFTA, and NITA) are not statistically significant and show an extremely high correlation with the solvency ratio and therefore were not considered in the regression.

Another conclusion to be drawn from this study is that the models with information closer to the bankruptcy date promote better results and, as more distant data are used from that date, the adjustment quality and the ability to differentiate between both groups of firms degrades. There are, however, some known problems related to the financial information reported by the firms (insufficiency, low quality, reliability), so that the results should be interpreted but always with due caution so that no erroneous inferences are made.

A possible future approach would be to analyze a larger sample that could better represent the study population, and a larger period could be considered, allowing to test either the effects of the 2007/8 crisis (Almamy et al., 2016) and the recent economic turmoil related to Covid-19 (Díez et al., 2021). Alternatively, other modeling techniques could be used to predict bankruptcy, namely different variants of MDA (Altman, Conan, and Holder, Tafler, Springate and Zmijewski), as done recently by Bărbuță-Mișu and Madaleno (2020) or neural network models (Abidin et al., 2021). Also, one promising methodology to use in the future is to implement machine-learning and big-data analyses (Le & Viviani, 2018; Alaka et al., 2020) to develop innovative business failure prediction, models.

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