THE INFLUENCE OF FINANCIAL FACTORS AND THEIR STABILITY ON THE PREDICTIONS OF FAILURE AND FINANCIAL DISTRESS: THE EVIDENCE FROM PORTUGUESE SMALL AND MEDIUM-SIZED ENTERPRISES IN HIGH AND MEDIUM-HIGH TECHNOLOGY MANUFACTURING SECTORS

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ABSTRACT

Using the traditional logistic regression model, this paper studies the impacts of some financial variables and the relative variance variables on the prediction of failure and financial distress of Portuguese small and medium-sized enterprises in high and medium-high technology manufacturing sectors. The results show that adding variance variables (standard deviations as the representative of variable stability) to the original variables does increase the classification accuracy of the models. As for the detailed impacts of financial factors, profitability as a positive factor is the most important indicator for both failure and financial distress, which is followed by debt structure and liquidity; on the other hand, different to leverage and firm size, intangible assets are more important in the distress prediction model compared to the failure prediction model. The differences of the statistically significant variables in the failure prediction model and the financial distress prediction model verify that it is necessary to separate failure from financial distress when doing predictions.

Keywords: Financial Factors and Stability, Predictions of Failure and Financial Distress, Small and Medium-Sized Enterprises, High and Medium-High Technology Manufacturing Sectors.

INTRODUCTION

Since the recent world financial crisis, the unstable business environment has made the research on business failure and bankruptcy prediction more important for investors and creditors (Pervan & Kuvek, 2013; Alaminos et al., 2016). Business failure not only could cause large economic and social losses for stakeholders, but also may lead to severe domestic crisis because of inefficient allocation of domestic capital (Laitinen & Suvas, 2013); on the other hand, financial distress diagnosis and prediction can significantly influence the operation and related parties (such as, credit institutions and stockholders) of a firm and even the whole economy of a country at large (Doumpos & Zopounidis, 1999). In concrete, accurate business failure prediction models can increase people's confidence in investment, lending and developing business relationships, and will promote the stability of economic growth (Gepp & Kumar, 2008).

As pointed out by Gepp & Kumar (2008), business failure prediction is the process to develop models in order to predict the financial failure of a business before it actually happens;

and, because of its usefulness and value of in the real world, business failure prediction is widely studied from both industry and academia. However, although the research topics of financial distress and bankruptcy have been studied for several decades since mid-1960s, new challenges have constantly appeared regarding the factors and impacts on the success or failure of firms (Maripuu & Männasoo, 2014); and from the perspective of the literature regarding financial ratios, there is no consensus about the best accounting ratios to predict the likelihood of financial distress (Mossman et al., 1998).

Being unable to meet obligations and the value a company's liabilities beyond the value of its assets are two obvious hallmarks of financial distress, and the purpose of financial distress research is to identify the useful accounting information in predicting future financial distress (Omelka et al., 2013; Ward & Foster, 1997). Here, the difference between business failure and financial distress should be stressed: that is, financial distress means financial problems which not necessarily result in bankruptcy (Achim et al., 2016; Pozzoli & Paolone, 2016); by contrast, although there is no unique definition of failure (Fernández-Gámez et al., 2016), discontinuity of operation is a mutual feature of different definitions of failure (Dimitras et al., 1996).

As is shown in the study of Gupta et al. (2018), there exist differences in influential factors in predicting bankruptcy and financial distress. Besides, compared to large listed firms, small firms are less researched in the literature (Pompe & Bilderbeek, 2005). It is also necessary to develop country-specific prediction models and apply models in different economic sectors in order to reflect different country's economic and business status (Šlefendorfas, 2016; Kanapickiene & Marcinkevicius, 2014). Therefore, this paper investigates the failure and financial distress of Portuguese small and medium-sized enterprises (SMEs) in high and medium-high technology manufacturing sectors.

As stated by Pacheco (2015), in 2012, 99.9% of Portuguese enterprises were SMEs, which contributed to 78% of the employees in the private sectors and 58% of the total turnover; according to the Caixa Bank Research reported by Pinheiro (2019) based on the data from Eurostat and the Bank of Portugal, in manufacturing industry, the firms in high and medium-high technology sectors contributed to about one fourth of the total sales in 2016. On the other hand, in Portugal SMEs have higher failure rate than large firms, and the failure rates of the Portuguese firms in high and medium-high technology sectors are higher than the failure rate in medium-low technology sectors (Succurro & Mannarino, 2014). So the first contribution of this paper is to help Portuguese high and medium-high technology SMEs to find significant financial indicators for predicting failure and financial distress.

The research of Dambolena & Khoury (1980) shows that: the stability of ratios can help to improve the ability to predict failure. Thus, in addition to the original financial ratios, this paper also takes the stability of ratios into account, which leads to the second contribution (that is, proffering empirical evidence to the usefulness of the stability of ratios in the prediction models). In particular, logistic regression analysis is used in the prediction models for the data of one, two and three years prior to the event; this three-year prediction method was used in the studies of (for instance) Mossman et al. (1998), Fernández-Gámez et al. (2016) and Alaminos et al. (2016). We also refer to the research method of Pompe & Bilderbeek (2005) in which the impacts of the stability of ratios (for example the standard deviation of three years) in three successive annual reports are explored in the prediction models. The followings of this paper are arranged in this order: literature review; data, variables, and research methodology; results and discussion; and conclusions.

LITERATURE REVIEW

The research on business failure can be traced back to 1930s (Pervan & Kuvek, 2013); however, it is since 1960s that statistical and mathematical models have been built for business failure prediction (Gepp & Kumar, 2008). As stated by Mossman et al. (1998), the models of using financial ratios to predict bankruptcy are firstly developed by Beaver and Altman (1968). Haber (2005) points out the difference between the research of Beaver (1966) and the research of Altman's (1968): that is, the previous one focuses on financial distress and insolvency and latter one pays attention to bankruptcy; and it is the application of sophisticated statistical technique (namely multiple discriminant analysis) that makes Altman (1968) research as one milestone of the bankruptcy study, which is different to the univariate technique introduced by Beaver (1966) for classifying firms in two groups by using financial ratios (Dimitras et al., 1996).

On the basis of companies' financial characteristics (financial ratios), multivariate discriminant analysis calculates the discriminant score to classify companies into healthy and bankrupt categories (Fejér-Király, 2015). However, multiple discriminate analysis requires for normality of predictors and the same variance-covariance matrices for both groups (Pervan & Kuvek, 2013). In order to overcome the limitations of the linear discriminant analysis approach, Ohlson (1980) begun to use logistic regression in the prediction of failure (Charitou et al., 2004); after that, data mining techniques (such as, neural networks, case-based reasoning, and decision trees) are applied in bankruptcy prediction models (Mihalovič, 2016).

Logit model is one of the most commonly used methods in bankruptcy prediction (Bauweraerts, 2016). Arnis et al. (2018, p.118) state that, "The Logit model is a nonlinear regression model specifically designed to assess dependent binary variables. It gives the probability that the dependent variable will get the value 1, given the values of the independent variables, by adopting techniques that lead the values being assessed to move in the range (0,1)." It is further explained by Kanapickiene & Marcinkevicius (2014) that: "In logistic regression models the bankruptcy probability is calculated by the following formula: P(Z)=1/(1+e-Z), where P is bankruptcy probability (from 0 to 1), and Z is Z value of the analyzed model. When P > 50%, there is a bankruptcy probability; when P ≤ 50%, there isn't any bankruptcy threat to a company." Logit analysis does not require to fulfill the requirements of linear discriminant analysis, such as, the multivariate normal distribution of the variables and the equivalence of the variance and covariance matrices of the variables for the non-failed and failed firms; notwithstanding that, logit models still have some limitations including multicollinearity problem and the problems of outliers and missing values (Giacosa et al., 2016).

DATA, VARIABLES, AND RESEARCH METHODOLOGY

The Portuguese small and medium-sized enterprises (SMEs) in the high technology and medium-high technology manufacturing sectors are chosen from the Iberian Balance Sheet Analysis System (SABI; developed by Bureau Van Dijk) database for building the sample. According to the criteria of European Union, here SME is defined as: number of employees less than 250; and turnover less than or equal to 50 million Euros or balance sheet total less than or equal to 43 million Euros. Based on the classification of NACE Rev. 2 2-digit level (from Eurostat), high technology manufacturing sectors include manufacture of basic pharmaceutical products and pharmaceutical preparations and manufacture of computer, electronic and optical products while medium-high technology manufacturing sectors contain manufacture of chemicals and chemical products, manufacture of electrical equipment, manufacture of machinery and equipment n.e.c., manufacture of motor vehicles, trailers and semi-trailers, and manufacture of other transport equipment.

It is required that all the candidate SMEs must report operating revenues in 2013, 2014, and 2015 to SABI database (in the observed five years from 2013 to 2017); and the data in 2016 and 2017 are used to identify the failed firms, financially distressed firms, and financially healthy firms. In concrete, the identifying method of Quintiliani (2017) is referred to for differentiating the financially distressed firms to the financially healthy firms: that is, "we consider as financial distress companies those that meet some of the following conditions: (i) its earnings before interest and taxes depreciation and amortization (EBITDA) are lower than its financial expenses for two consecutive years; and/or (ii) increase in the debt-to-net worth formula for two consecutive periods with concomitant decrease of the denominator." Following the above criteria, here the financially healthy firms are the "active" firms with higher EBITDA (compared to financial expenses), decrease in debt ratio, and increase in net worth. As for the failed firms, we follow both the identifying methods of Pacheco (2015) and Mata and Portugal (1994): failed firms are the firms that are not labeled as "active" firms in SABI database (discriminating from the firms labeled as "active") and do not report operating revenues in 2016 and 2017 two consecutive years.

In order to find the significant financial factors separately in the failure and financial distress prediction models, we classify the total sample into two groups: the failure group (for comparing the financially healthy firms with the failed firms) and the financial distress group (for comparing the financially healthy firms with the financially distressed firms). Binary logit regression model is employed here, as it is suitable for the dichotomous dependent variable and the explanatory variables can be quantitative or qualitative (Brédart, 2014). In particular, referring to the research method of Pompe & Bilderbeek (2005) where the independent variables are identified into four groups (the ratios in year 1; the ratios and standard deviations in year 1; the ratios in year 3; and the ratios and standard deviations in year 3), we also run regression four times respectively with only the 2015 original data, only the 2013 original data, the 2015 original data together with the variance variables, and the 2013 original data together with the variance variables. The variance variables are the standard deviations of the 2013, 2014 and 2015 original data.

Since logit model is employed here, it is necessary to avoid multi-linearity problem when choosing independent variables. Financial ratios, however, usually are internally related. So, instead of grabbing a bunch of financial ratios to describe one category of financial characteristic, we choose the most commonly used financial ratios (or variables) to represent financial characteristics, which would reduce the number of independent variables. As pointed out by Blanco-Oliver et al. (2015), traditionally, leverage and debt related ratios are strong predictors related to bankruptcy and financial risk, and heavy liabilities may cause financial problems; in addition, profitability ratios represent the ability of firms to accumulate reserves and are widely used in the prediction of bankruptcy. Low liquidity and being difficult to meet the commitments are the common features of distressed firms, so liquidity-related variables are also necessary for measuring the capacity of a firm to pay its debts and to continue its activity (Brédart, 2014). Thus, indebtedness, the ratio of current liabilities to total liabilities, return on assets (ROA), and general liquidity are used in this paper for respectively representing leverage, debt structure, profitability, and liquidity.

Because we focus on the SMEs in high and medium-high technology sectors, it is necessary to consider the influence of intangible assets which play an important role (Elston & Audretsch, 2011); considering that many firms in the sample do not report intangible assets, a dummy variable is created. Firm size (total assets) and assets structure (tangible fixed assets) are also included in this study. The definitions of the variables and the statistics of the sample are shown in Table 1, 2 and 3. On average, compared to the financially distressed firms, the financially healthy firms show higher total assets, higher ROA, higher proportion of tangible fixed assets, higher proportion of firms with intangible assets, and lower liquidity. In the failure group, generally it shows similar situation, aside from financially healthy firms showing obviously lower leverage and higher proportion of current liabilities.

Table 1
VARIABLE DEFINITIONS

Dependent variable (1): failure or financial health	Failed firms are the "inactive" firms that report operating revenues in 2013, 2014, and 2015 but not report operating revenues in 2016 and 2017. Financially healthy firms are the "active" firms with higher EBITDA (compared to financial expenses), continuous decrease in debt ratio, and continuous increase in net worth from 2013 to 2017. Note: the failed firms only report operating revenues in 2013, 2014, and 2015, while the financially healthy firms report operating revenues in all the five years from 2013 to 2017.
Dependent variable (2): financial distress or financial health	Financially distressed firms are those that meet some of the following conditions: (i) its earnings before interest and taxes depreciation and amortization (EBITDA) are lower than its financial expenses in both 2016 and 2017; and/or (ii) increase in the debt-to-net worth formula from 2016 to 2017 with concomitant decrease of the denominator; and these conditions do not appear in 2013, 2014, and 2015 (based on the classifying method of Quintiliani (2017, pp. 71-72)). Financially healthy firms are the "active" firms with higher EBITDA (compared to financial expenses), continuous decrease in debt ratio, and continuous increase in net worth from 2013 to 2017. Note: both the financially distressed firms and the financially healthy firms must report operating revenues in all the five years from 2013 to 2017.
Independent variables	
Firm size	Natural logarithm of total assets (in thousands of Euros); Ln assets
Profitability	ROA (return on assets): Profits before tax/Total assets
Liquidity	General liquidity (current ratio): the ratio of current assets to current liabilities
Solvency (leverage)	Indebtedness: (Total shareholders funds and liabilities—Shareholders equity)/Total shareholders funds and liabilities
Intangibles	Dummy variable of intangible assets (if firm's intangible assets are more than zero, it equals 1; if not, it equals 0)
Tangibles (assets structure)	The ratio of tangible fixed assets to total assets
Liability structure	The ratio of current liabilities to total liabilities

Table 2
THE STATISTICS OF THE SAMPLE DATA IN THE FINANCIAL DISTRESS GROUP (250 CASES)

Variables	Mean	Standard Deviation	Min	Max	The mean of financially distressed firms (60 cases)	The mean of financially healthy firms (190 cases)
Ln assets 2015	6.691	1.602	2.381	10.585	6.471	6.760
Ln assets 2013	6.568	1.619	2.226	10.777	6.370	6.631
Standard deviation of in assets	0.134	0.141	0.000	0.928	0.146	0.131
ROA 2015	0.097	0.104	-0.164	0.663	0.041	0.114

ROA 2013	0.047	0.105	-0.816	0.371	-0.001	0.063
Standard deviation of ROA	0.054	0.071	0.000	0.603	0.073	0.047
Indebtedness 2015	0.627	0.326	0.014	2.753	0.674	0.611
Indebtedness 2013	0.776	0.557	0.024	6.491	0.764	0.779
Standard deviation of indebtedness	0.088	0.181	0.000	2.466	0.090	0.087
Tangibles 2015	0.237	0.205	0.000	0.866	0.227	0.240
Tangibles 2013	0.247	0.211	0.000	0.967	0.245	0.248
Standard deviation of tangibles	0.040	0.048	0.000	0.366	0.049	0.037
Dummy intangibles 2015	0.332	0.472	0.000	1.000	0.233	0.363
Dummy intangibles 2013	0.352	0.479	0.000	1.000	0.283	0.374
Current liabilities to total liabilities 2015	0.699	0.272	0.054	1.000	0.692	0.701
Current liabilities to total liabilities 2013	0.724	0.270	0.005	1.000	0.775	0.709
Standard deviation of current liabilities to total liabilities	0.082	0.100	0.000	0.474	0.114	0.072
General liquidity 2015	3.018	5.470	0.348	72.558	4.047	2.693
General liquidity 2013	2.359	3.843	0.106	39.628	3.181	2.100
Standard deviation of general liquidity	0.946	3.581	0.000	46.861	2.134	0.5707

Table 3
THE STATISTICS OF THE SAMPLE DATA IN THE FAILURE GROUP (236 CASES)

Variables	Mean	Standard Deviation	Min	Max	The mean of Failed firms (46 cases)	The mean of financially healthy firms (190 cases)
Ln assets 2015	6.400	1.764	0.798	10.585	4.914	6.760
Ln assets 2013	6.354	1.729	-0.564	10.777	5.212	6.631
Standard deviation of ln assets	0.179	0.250	0.000	1.864	0.379	0.131
ROA 2015	-0.073	1.403	-20.241	0.663	-0.844	0.114
ROA 2013	-0.067	1.643	-25.054	0.977	-0.601	0.063
Standard deviation of ROA	0.192	1.141	0.000	12.904	0.791	0.047
Indebtedness 2015	1.104	2.315	0.027	20.333	3.136	0.611
Indebtedness 2013	1.149	2.604	0.049	29.113	2.678	0.779
Standard deviation of indebtedness	0.328	1.330	0.000	12.883	1.322	0.087
Tangibles 2015	0.215	0.213	0.000	0.866	0.114	0.240
Tangibles 2013	0.228	0.214	0.000	0.891	0.147	0.248
Standard deviation of tangibles	0.037	0.050	0.000	0.447	0.039	0.037
Dummy intangibles 2015	0.318	0.467	0.000	1.000	0.130	0.363
Dummy intangibles 2013	0.347	0.477	0.000	1.000	0.239	0.374
Current liabilities to total liabilities 2015	0.696	0.285	0.016	1.000	0.678	0.701
Current liabilities to total liabilities 2013	0.701	0.285	0.007	1.000	0.670	0.709
Standard deviation of current liabilities to total liabilities	0.076	0.097	0.000	0.522	0.092	0.072

General liquidity 2015	3.067	4.875	0.049	52.772	4.611	2.693
General liquidity 2013	2.390	3.021	0.039	25.916	3.591	2.010
Standard deviation of general liquidity	0.898	2.420	0.000	27.734	2.252	0.571

RESULTS AND DISCUSSION

The failure group (including the financially healthy firms and the failed firms) and the financial distress group (including the financially healthy firms and the financially distressed firms) are separately put into the binary logit models. In concrete, each group has four regressions with different independent variables (the 2015 original variables, the 2013 original variables, the 2015 original variables together with the standard deviations of the 2013, 2014 and 2015 data, and the 2013 original variables together with the standard deviations of the 2013, 2014 and 2015 data). The detailed results are shown in the following four tables. Here we believe that one variable is statistically significant if its P-value is lower than 0.1.

The Results of Logistic Regressions of the Failure Group

Table 4
THE RESULTS OF LOGISTIC REGRESSIONS OF THE FAILURE GROUP (ONLY ORIGINAL VARIABLES)

Independent variables	2015 data		2013 data	
	Number of observations: 236		Number of observations: 236	
	LR chi2(7): 146.96		LR chi2(7): 48.72	
	Prob > chi2: 0.0000		Prob > chi2: 0.0000	
	Log likelihood: -42.9299		Log likelihood: -92.0532	
	Pseudo R2: 0.6312		Pseudo R2: 0.2092	
	Classification accuracy 93.22%		Classification accuracy 85.59%	
	Coefficients	P>|z|	Coefficients	P>|z|
Ln total assets	-0.542	0.052	-0.415	0.005
ROA	-17.639	0.000	-3.513	0.030
Indebtedness	2.051	0.000	0.149	0.328
Tangibles to total assets	0.242	0.884	-0.792	0.507
Intangibles dummy	-0.604	0.424	-0.010	0.984
Current liabilities to total liabilities	2.683	0.023	0.049	0.948
General liquidity	0.256	0.000	0.177	0.009
Constant	-1.894	0.294	0.655	0.527
Note: the positive sign of coefficient means being positively related to the likelihood of failure (or distress); thus being negatively related to financial health.				

In the failure group of the original variables, the classification accuracy of the 2015 regression (93.22%) is higher than that of the 2013 regression (85.59%). In concrete, there are five statistically significant variables in the 2015 regression (four variables' significance being lower than 0.05; one variable's significance being between 0.05 and 0.1), while three variables show statistical significance in the 2013 regression (significance all being lower than 0.05).

Among the statistically significant variables, total assets and ROA are negatively related to the probability of failure; on the other hand, liquidity, indebtedness, and the ratio of current liabilities to total liabilities are positively related to the probability of failure (although indebtedness and the ratio of current liabilities to total liabilities only show statistical significance in the 2015 regression).

Table 5
THE RESULTS OF LOGISTIC REGRESSIONS OF THE FAILURE GROUP (ORIGINAL AND VARIANCE VARIABLES)

Independent variables	2015 data		2013 data	
	Number of observations: 236		Number of observations: 236	
	LR chi2(13): 170.84		LR chi2(13): 112.26	
	Prob > chi2: 0.0000		Prob > chi2: 0.0000	
	Log likelihood: -30.9942		Log likelihood: -60.2825	
	Pseudo R2: 0.7338		Pseudo R2: 0.4822	
	Classification accuracy 94.92%		Classification accuracy 91.10%	
	Coefficients	P>|z|	Coefficients	P>|z|
Ln total assets	-0.688	0.045	-0.147	0.479
Ln total assets standard deviation	3.025	0.136	2.576	0.113
ROA	-28.947	0.000	-11.828	0.000
ROA standard deviation	25.484	0.001	14.957	0.000
Indebtedness	-0.266	0.757	-1.014	0.094
Indebtedness standard deviation	0.418	0.638	2.640	0.110
Tangibles	2.047	0.329	1.514	0.355
Tangibles standard deviation	-9.672	0.425	-8.503	0.189
Intangibles dummy	-0.004	0.997	-0.229	0.718
Current liabilities to total liabilities	3.050	0.049	0.549	0.601
Current liabilities to total liabilities standard deviation	1.588	0.663	-3.975	0.186
General liquidity	0.144	0.339	0.152	0.137
General liquidity standard deviation	0.338	0.223	0.360	0.003
Constant	-1.172	0.672	-2.268	0.171
Note: because we set intangibles as dummy variable, it is not necessary to calculate its standard deviation.				

In the failure group of the original and variance variables, the classification accuracy of the 2015 regression (94.92%) again is higher than that of the 2013 regression (91.10%). There are four statistically significant variables in the 2015 regression (all of the significance being lower than 0.05); four variables show statistical significance in the 2013 regression (three variables' significance being lower than 0.05; one variable's significance being between 0.05 and 0.1).

Among the statistically significant variables, total assets, ROA and indebtedness are negatively related to the probability of failure, whereas the ratio of current liabilities to total liabilities as well as the variance variables of ROA and liquidity are positively related to the probability of failure. Here, only ROA and its variance variable show statistical significance in both the regressions of 2013 and 2015; thus, both the profitability and its stability are important.

In either the 2015 regressions or the 2013 regressions, the regression with both the original and variance variables generates higher classification accuracy than the regression only with the original variables; therefore, introducing variance variables into the model tends to increase the classification accuracy, especially in the 2013 regressions.

The Results of Logistic Regressions of the Financial Distress Group

Table 6
THE RESULTS OF LOGISTIC REGRESSIONS OF THE FINANCIAL DISTRESS GROUP (ONLY ORIGINAL VARIABLES)

Independent variables	2015 data		2013 data	
	Number of observations: 250		Number of observations: 250	
	LR chi2(7): 44.24		LR chi2(7): 30.13	
	Prob > chi2: 0.0000		Prob > chi2: 0.0001	
	Log likelihood: -115.6515		Log likelihood: -122.7057	
	Pseudo R2: 0.1605		Pseudo R2: 0.1093	
	Classification accuracy 78.80%		Classification accuracy 80.40%	
	Coefficients	P>|z|	Coefficients	P>|z|
Ln total assets	0.000251	0.998	-0.010	0.940
ROA	-14.500	0.000	-8.051	0.001
Indebtedness	0.417	0.433	0.085	0.823
Tangibles to total assets	-1.066	0.222	0.249	0.773
Intangibles dummy	-0.757	0.065	-0.333	0.387
Current liabilities to total liabilities	0.494	0.412	1.821	0.009
General liquidity	0.029	0.408	0.097	0.056
Constant	-0.365	0.751	-2.384	0.039

In the distress group of the original variables, the classification accuracy of the 2015 regression (78.80%) is lower than that of the 2013 regression (80.40%). In particular, there are two statistically significant variables in the 2015 regression (one variable's significance being lower than 0.05; the other variable's significance being between 0.05 and 0.1), whereas three variables show statistical significance in the 2013 regression (two variables' significance being lower than 0.05; one variable's significance being between 0.05 and 0.1).

Among the statistically significant variables, ROA is negatively related to the probability of distress in both the 2015 and 2013 regressions; intangibles dummy is also negatively related to the probability of distress but only in the 2015 regression. The ratio of current liabilities to total liabilities and liquidity are positively related to the probability of distress only in the 2013 regression.

Table 7
THE RESULTS OF LOGISTIC REGRESSIONS OF THE FINANCIAL DISTRESS GROUP (ORIGINAL AND VARIANCE VARIABLES)

Independent variables	2015 data		2013 data	
	Number of observations: 250		Number of observations: 250	
	LR chi2(13): 72.23		LR chi2(13): 37.90	
	Prob > chi2: 0.0000		Prob > chi2: 0.0003	
	Log likelihood: -101.6534		Log likelihood: -118.8199	
	Pseudo R2: 0.2622		Pseudo R2: 0.1375	
	Classification accuracy 83.60%		Classification accuracy 80.80%	
	Coefficients	P>|z|	Coefficients	P>|z|
Ln total assets	0.092	0.522	0.016	0.907
Ln total assets standard deviation	-0.159	0.931	-1.429	0.394
ROA	-18.253	0.000	-6.942	0.004
ROA standard deviation	14.710	0.001	1.433	0.711
Indebtedness	0.054	0.932	-0.144	0.814
Indebtedness standard deviation	0.369	0.881	0.335	0.879
Tangibles	-1.299	0.208	-0.555	0.574

Tangibles standard deviation	2.335	0.652	2.509	0.539
Intangibles dummy	-0.683	0.124	-0.304	0.445
Current liabilities to total liabilities	0.896	0.213	1.542	0.043
Current liabilities to total liabilities standard deviation	3.576	0.064	2.510	0.144
General liquidity	0.013	0.778	-0.089	0.541
General liquidity standard deviation	0.030	0.696	0.274	0.205
Constant	-1.795	0.190	-2.064	0.143

In the distress group of the original and variance variables, the classification accuracy of the 2015 regression (83.60%) is higher than that of the 2013 regression (80.80%). There are three statistically significant variables in the 2015 regression (two variables' significance being lower than 0.05; one variable' significance being between 0.05 and 0.1), while two variables show statistical significance in the 2013 regression (the significance of both being lower than 0.05).

Among the statistically significant variables, only ROA (being negatively related to the probability of distress) is statistically significant in both the 2015 and 2013 regressions. The ratio of current liabilities to total liabilities as well as the variance variables of ROA and the ratio of current liabilities to total liabilities are positively related to the probability of distress.

In either the 2015 regressions or the 2013 regressions, the regression with both the original and variance variables generates higher classification accuracy than the regression only with the original variables. On the other hand, compared to the 2013 regressions, the 2015 regressions show higher classification accuracy in all the models expect for the model of financial distress group with the original variables; similar results (that the percentage of correct prediction tends to decrease when using long-term data compared to short-term data but this is not necessarily monotonous) are also found by Machek (2014) who compares the predictive ability of different prediction methods respectively in five-year, four-year and three-year periods.

DISCUSSION

Generally speaking, the model of failure prediction performs better than the model of financial distress prediction, not only because there are more statistically significant variables in the failure predictions but also because of showing higher classification accuracy. This result is not of surprise, for the reason that the differences between the financially healthy firms and the failed firms are more obvious than the differences between the financially healthy firms and the financially distressed firms (considering that financially distressed firms still keep on operating whereas failed firms do not generate operating revenues); for example, the average ROA of the failed firms is much lower than that of the financially distressed firms, while the average indebtedness of the failed firms is much higher than that of the financially distressed firms. The followings respectively discuss the statistically significant variables in the models of both the failure prediction and financial distress prediction; here, the variables with positive sign in coefficients (being positively related to the likelihood of failure or distress) are negative factors to firms, while the variables with negative sign in coefficients (being negatively related to the likelihood of failure or distress) are positive factors to firms.

Profitability is the most important positive factor for avoiding both failure and financial distress, as ROA shows statistical significance and negative coefficient sign in all the regressions; in addition, its variance variable is also of importance because of showing statistical significance in most regressions. The important role of profitability-related variables in predicting bankruptcy and failure is also highlighted in the research of Stundžienė & Boguslauskas (2006) and Charitou et al. (2004). As the source of retained earnings and internally generated funds, profits play a crucial role in keeping the financial health of high and medium-high technology SMEs, because of the possible financial and borrowing constraints.

Debt structure (the ratio of current liabilities to total liabilities) and liquidity are also important, serving as negative factors. The negative impact of current liabilities that is similar to the finding of Cenciarelli et al. (2018) means positive impact of non-current liabilities (or long-term debts); here, given the characteristics of high and medium-high technology SMEs that research and development as well as innovation activities usually require relatively longer time, it is reasonable that long-term debts are more suitable for this type of SMEs. As for the negative impact of liquidity, it could be interpreted as the negative impact of too much liquid assets. For instance, as pointed out by Cenciarelli et al. (2018), too many stocks accumulated and receivables uncollected from customers could reduce the operating cash flow and then influence the ability to repay debts. Compared to other SMEs, it is more necessary for high and medium-high technology SMEs to increase the efficiency of using limited funds and to reduce idle funds, when taking the financial constraints into account.

Leverage (indebtedness) and firm size (total assets) only show statistical significance in the regressions of failure group. In particular, the impact of firm size is more stable than that of leverage, since firm size keeps on working as a positive factor while the impact of leverage is unstable. The positive impact of firm size is to some extent in accord with the theory of efficient scale (that is, as stated by Audretsch & Mahmood (1995), cost disadvantage would be reduced when firm size gets close to the minimum efficient scale); and the result here is also close to the finding of Bauweraerts (2016), that is, firm size is negatively related to bankruptcy. In general, for larger firms, shrinking in size is an approach to avoid exit or alleviate distress when in inefficient situations (Mata & Portugal, 1994); in particular, larger size and more funds should be especially important for high and medium-high technology SMEs to introduce high-technology equipment and attract intelligent employees for producing good-quality products.

As for leverage, the positive impact (with the statistical significance level close to 0.1) appears in the 2013 regression with variance variables, which is three years prior to the failure event; by contrast, the negative impact (with the statistical significance level being lower than 0.05) is shown in the 2015 regression without variance variables, which is one year before the failure event. So whether leverage can take benefits depends on the situations faced by the firms. Higher leverage represents higher borrowed funds (which should be helpful to the financially constrained high and medium-high technology SMEs), whereas the heavy burden of paying back interests and loans would be unbearable when being overdue. In fact, as pointed out by Omelka et al. (2013), although generally speaking financial leverage can reflect the capital structure and financial risk of a company, it is necessary to consider the concrete situation of financial leverage when researching on the impact of its change; for example, short-time high indebtedness may not mean a financial distress in the case of company’s debt-financed expansion.

Intangible assets work as a statistically significant positive indicator in one regression in the model of financial distress prediction. This may be because intangible assets can take positive effects to the firms keeping on operating (rather than the firms going to cease generating revenues), considering that intangible assets usually take long-term effects (rather than short-run productivity and profitability; Chappell & Jaffe (2018)). Not with standing that, the impact of intangible assets is relatively weak; this may be caused by the insufficiency in funds for high and medium-high technology SMEs to create intangible assets. Furthermore, as pointed out by Tiron-Tudor et al.

(2014), the uncertainty of intangibles' valuation and the variance of intangibles' structure in different sectors could also muddy the impacts of intangible assets. As for tangible fixed assets, no statistical significance is observed in any regression, which may to some extent illustrate that tangible fixed assets are not as important as intangible assets to high and medium-high technology SMEs.

CONCLUSION

This paper studies the impacts of some financial variables and the relative variance variables on the predictions of failure and financial distress of Portuguese SMEs in high and medium-high technology manufacturing sectors. The results show that: adding variance variables to the original variables does increase the classification accuracy of the models, which corresponds to the research result of Dambolena & Khoury (1980) that the stability of ratios can help to improve the ability to predict failure. The results here also challenge the study of Mossman et al. (1998) who find that standard deviation models do not perform as well as other models (including the financial ratio model).

In terms of the difference between the failure and financial distress prediction models, following the research of Gupta et al. (2018) who find different impacts of factors in predicting bankruptcy and financial distress, we also find that (aside from ROA which works as a statistically significant positive indicator in all the regressions) there are more statistically significant variables in the failure prediction model than in the financial distress prediction model. This may be because, contrasting the failed firms and the financially distressed firms, the financially distressed firms are more close to the financially healthy firms due to both keeping on generating operating revenues. Hence, the more differences there are between the two categories in the dependent variable (here in logistic model), the more obvious differences the regression results show. Although the results that we obtain are clear, the smallness in sample size may to some extent limit the prevalence of the results of this paper. So it is advised to research on more countries, which can not only enlarge the sample size but also help to develop country-specific models.

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