

CORPORATE FAILURE: BANKRUPTCY PREDICTION FOR ITALIAN SMES BASED ON A LONGITUDINAL CASE STUDY FROM 2000 TO 2011

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Abstract

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We investigate the case of Small-Medium Enterprises (SMEs) in Italy trying to understand if key performance indicators obtained from the financial statement are able to predict possible distress in a company with enough time to take some corrective actions. In order to test the hypotheses, a nonparametric supervised classification algorithm has been applied to a random sample of 100 non-listed SMEs, considering 50 companies that filed for bankruptcy during the period 2000-2011 and 50 companies still active on the market at the end of 2011. Results describe the Italian picture for SMEs during an economic crisis period. They show that, for the Italian case, it is possible to predict with enough time (4-5 years prior to failure) a distress situation in a firm through classification methods. Anyway, these methods are not predicting the health of a company but the possibility of the firm to access the credit system. The results are limited to the Italian SMEs context which is quite particular if compared with other countries in Europe. The dataset is limited in size but has been chosen to be representative of non-listed Italian companies.

Keywords: Financial Ratios, Financial Crisis, Bankruptcy, SMEs, Performance Indicators, Nonparametric Classifier, Supervised Classification

Authors' individual contribution: Conceptualization - F.di D.; Methodology - L.N.; Writing - F.di D. and L.N.; Investigation - L.N.; Funding - F.di D.; Resources - F.di D. and L.N.; Supervision - L.N.

1. INTRODUCTION

Accounting ratios come from financial information included in financial statements that companies are obliged to produce for external stakeholders and to be compliant with the law and fiscal rules. They can have a prediction role for companies' bankruptcy (Barnes, 1987).

Bankruptcy can be defined as the lack of resources to repay the obligations of a company as they come due (Boardman, Bartley, & Ratliff, 1981).

Many studies have been devoted to the use of accounting data in order to predict corporates bankruptcy, starting from Beaver's (1966), and Altman's (1968) research. Beaver used univariate statistics in the US market while Altman found out

that this kind of analysis is not good enough for evaluating companies' potential failure. For this reason, he introduced the Multiple Discriminant Analysis (MDA) in order to predict the possibility of a company to fail. Anyway, this analysis does not consider the evolution of financial ratios over time. Ohlson (1980), to solve this issue, used information about the company's performance at a different time before failure.

In the US context, Altman's model was used by many researchers to predict big companies' failure (Blum, 1974; Ohlson, 1980). The survival of a firm is linked to economic and financial equilibrium in the medium-long term, where economic balance refers to the capability to generate revenues higher than costs and to produce a profit for shareholders'

compensation, while financial equilibrium refers to the generation of cash inflows higher than outflows.

Mainly, the survival of a firm is guaranteed by the economic balance in the medium-long term, even if the company can suffer from some financial distress in the short term. The opposite is not true, that is, if a company does not have economic equilibrium in the medium-long term, it will not survive even with a financial balance in the short term.

Of course, in the long run, the failure of a company will depend on the influence of both situations (Nieddu & Patrizi, 2000; Bhimani, Gulamhussen, & da Rocha Lopes, 2013):

1. On the economic side, the lack of profits (i.e. negative or very low income and profitability).

2. On the financial side, the lack of financial resources to repay the obligations when they come due (i.e. no cash, low solidity, and very high leverage).

2. LITERATURE REVIEW AND HYPOTHESES

In literature, the use of accounting ratios to predict possible distress situations has been mainly focused on large companies. Few studies have analyzed the small-medium firms' (SMEs) failure before the important study of Storey, Keasey, Watson, and Wynarczk (1987).

In general, it is not very common to study SMEs' failure. They are mostly under-capitalized and depend on banks' financial funds because the main shareholders do not have enough resources to invest in the company.

For this reason, it is of utmost importance to establish the possibility to predict SMEs' failure. In fact, a prediction model to evaluate the risk of their failure in advance would be very helpful both for the companies receiving loans from the banks and for the financial institutions themselves. Financial statement analysis has been mainly used by lenders to evaluate the creditworthiness of the borrowers. In fact, using a good model, banks and other financial institutions could avoid lending to companies that are likely to fail, and thus never repay their loans. With the possibility to predict the failure in advance, banks and financial institutions could establish a long-term relationship with companies that have a lower risk to fail (according to the prediction model), reducing their own risk to lose the borrowed capital.

In order to have an effective bankruptcy prediction method, it is important to evaluate how long time ahead of the model is able to accurately predict failure. Many studies have a high accuracy rate only one or two years prior to failure because the closer in time ratios are generally very representative of a company's deteriorating health conditions. Unfortunately, in general, one year prior to failure the firm situation is already compromised, so it could be too late to implement any action to recover (di Donato & Nieddu, 2014). Furthermore, a model able to predict bankruptcy two years prior to failure (Deakin, 1972) could be not useful because only two years in advance is not enough time to allow a lending institution to release itself without facing the risk of a significant loan loss (Casey, 1980).

The aim of this paper is to study the usefulness of accounting ratios in predicting the possible failure of a SME with enough time to take some effective actions for a feasible recovery.

In this case, it is acceptable to think that failing firms must have some similar characteristics that tend to group the companies together and that these features are reflected in their performance ratios. It goes without saying that not all performance ratios function in the same way: some companies may fail, for example, because they do not repay their loans and some others may fail because they do not generate revenues higher than costs. Even if they are a different kind of distress, both of these situations can cause the failure of a firm. A broad set of accounting ratios should be able to get all the information on the health of a company. Therefore, the first hypothesis to test is:

H1: Accounting ratios can be utilized to predict corporate bankruptcy with enough time to allow for corrective actions.

In general, profitability ratios measure the capability of a company to generate revenues higher than costs, also producing a compensation for the shareholders. They assess the survival of the firm in the long-term period.

If the first hypothesis will be verified, we will test the second hypothesis:

H2: Profitability ratios are more important than Financial Indicators in order to predict the health of a company.

Both hypotheses will be tested on the original data set collected over 12 years (2000-2011) for a stratified sample of non-listed small-medium Italian companies. Considering that the purpose of the paper is to establish if accounting ratios can predict bankruptcy early enough to take effective actions, these firms will be analyzed at various point in time prior to a failure situation (up to 8 years) and they will be matched with healthy companies from the same year. The comparison with a similar healthy firm is to control for other elements that cannot be taken into account such as the capability of the managers to implement some activities in order to deal with the crisis of the company.

The time period analyzed (2000-2011) also includes the year 2008, when a strong financial crisis affected many countries and many companies within these countries, especially small-medium enterprises. During a crisis, typically, the performance ratios should be more representative of the company's health. We then tested Italian SMEs across the 2008 financial crisis. The choice of this kind of firms is mainly due to the importance of SMEs in the Italian context and to the specificity of such SMEs. Our contribution has useful implications both for banks and SMEs that do not always have the full control of their financial situation. Banks and financial institutions could use these results in order to avoid lending to companies with a high risk to fail and to establish a long-term relationship with firms that have a lower risk to fail (according to the prediction model), without losing their borrowed capital.

It should be noted that researchers have used many approaches to bankruptcy prediction assessment. Although Jones (1987) highlighted that any methodology to predict bankruptcy should be

tested on a hold-out sample (Nieddu & Patrizi, 2000; McLachlan, 2004) of companies not used in the analysis, this advice has not been fully adopted in the literature. Even those few cases when the methods have been tested on a hold-out sample the results depend on the specific sample that has been selected. In the following experimental setup the performance of the classification algorithm will be tested using leave-one-out (Efron & Tibshirani, 1995; Nieddu & Patrizi, 2000), i.e. all the companies, in turn, will be tested on a classifier trained on independent data.

The layout of the paper is as follows: in Section 3 the original dataset is presented together with the selected features chosen from the data and used in the classification. In Section 4 the used nonparametric classifier is described and in Section 5 the results are presented. Finally, in Section 6 some conclusions are summarized.

3. THE DATA

3.1. The sample

To test the hypotheses in the paper the classification technique has been applied to a random sample of 100 non-listed SMEs, considering 50 companies that filed for bankruptcy during the period 2000-2011 and 50 companies still active on the market at the end of 2011. For each firm in the sample, more than one financial statement is available. For the still operating ones, at the end of the considered time period, a report for each year was available, while for the others only the financial statements up to the time of bankruptcy were available. The sample was randomly selected from the companies running their business in Italy. We considered only firms with revenues from sales in the range of 2 million - 50 million euros at the beginning of the considered period. As in Abdullah, Halim, and Rus (2008), we did not include financial and real estate companies because their ratios are highly volatile. Moreover, the ratios of these firms can be interpreted a bit differently because financial companies, for example, have different nature of income and expenses from non-financial companies. Out of 100 firms, 18 were randomly drawn from firms operating in the manufacturing sector (9 failed and 9 still operating at the end of the study), 8 from the construction sector (4 failed and 4 still operating at the end of the study) and 74 from the service sector (37 failed and 37 still in operation at the end of the study).

3.2. Feature selection

The accounting information used in this work was collected through an Italian Agency's database (www.cerved.com), related to the economic and financial data of Italian non-listed companies. For each company in the dataset, we have calculated the most common accounting ratios for every year in the period 2000-2011. According to Barnes (1987), we selected the ratios throughout the criterion of popularity, meaning their frequency of appearance in the literature (Bellovary, Giacomino, & Akers, 2007).

Moreover, we grouped the selected ratios considering the dimension of the company they assess (economic or financial), so that they have been classified into two groups:

1. Profitability ratios alone, related to the economic performance of the company: Return on Equity, Capital Turnover, Net Income/Total Assets, Return on Investment, Earning/Sales, Return on Sales, Financial Interests/Ebitda, Financial Interest/Sales.

2. Leverage and liquidity ratios alone, related to the financial performance of the company: Financial Debts/Equity, Short Term Bank Loan/Working Capital, Cash Flow/Total Debt, Structure Ratio 1, Structure Ratio 2, Working Capital/Total Assets, Quick Ratio, Working Capital Cycle, Financial Debt/Working Capital, Current Ratio, Retained Earnings/Total Assets.

We want to test the usefulness of the information on key performance indicators in predicting the possible future crisis. For this reason, we have conducted a cross-sectional study: all the failed companies have been considered at various years prior to failure (up to 8 years). Each distressed firm was randomly matched with a healthy firm belonging to the same industry sector and with a similar amount of total assets. Therefore at each time lag, we have a balanced sample of failed and non-failed companies. These criteria were set as control factors to guarantee minimum bias in the choice of the control sample used in the estimation of the classifier. In Table 1 the number of firms available at each time lag has been exhibited.

Table 1. Number of firms available at each time lag prior to failure

Time lag (years)	1	2	3	4	5	6	7	8
Number of firms	100	100	100	98	92	66	46	34

Since the matching of failed firms with healthy ones was carried out randomly, the selection mechanism has been repeated 300 times for each year lag to get an average estimate of the performance of each prediction technique. Failed companies have been considered from 1 up to 8 years prior to failure. It is clear that the sample size of failed firms decreased as the number of years prior to failure increased.

The correct recognition rate, sensitivity, and specificity have then been calculated. Since the matching between the failed companies and the healthy ones was carried out randomly 300 times, the performances that will be reported are average over 300 trials.

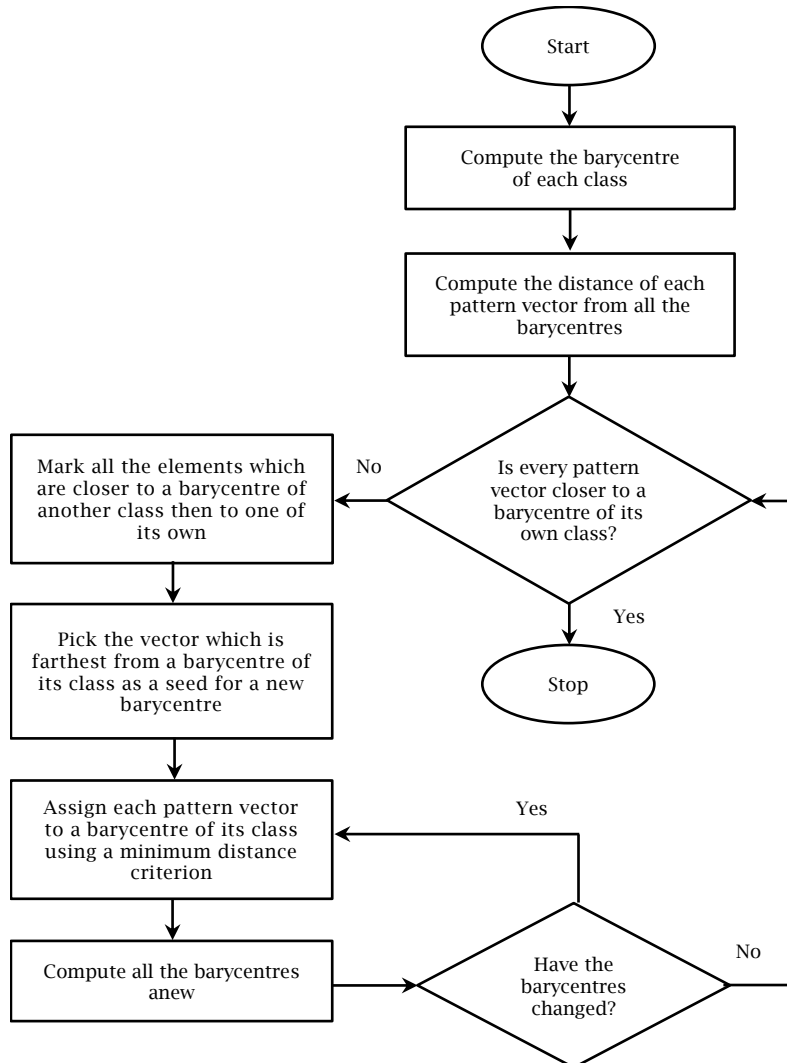
4. THE ALGORITHM

The classification algorithm used in this work is a nonparametric supervised classification algorithm that has been already used in several occasions and resulted to be very efficient and reliable (Nieddu & Patrizi, 2000). It does not make any special distributional assumption on the dataset. It is a slightly modified version of the k-means clustering algorithm with a constraint on how clusters are

formed. Namely, clusters are required to be homogenous with respect to the class of the elements that belong to a cluster. If that is not the case, then clusters are split and a k-means algorithm with an increased number of classes is performed

until all clusters are composed of elements from the same class. For a more detailed description of the algorithm see Nieddu and Patrizi (2000). The flow-chart of the algorithm is detailed in Figure 1.

Figure 1. Flow-chart of the algorithm



The algorithm will be trained on a dataset and its performance will be tested on an independent dataset. To determine the predictive ability of a classifier it must be tested on an independent sample of objects (firms) of known classes. Various aspects of the predictive ability can be considered, namely: correct recognition rate, sensitivity, and specificity. The correct recognition rate is an overall measure of the capability of the classifier to correctly classify new objects regardless of their status (healthy or in distress) while sensitivity and specificity are related to the ability of the classifier to correctly classify failed companies or to correctly classify nonfailed ones.

Sensitivity can be defined as the number of firms that are classified as failed (by the algorithm) as a proportion of the total number of failed firms in the dataset. It is, therefore, the ratio between the number of failed firms that have been classified as failed by the algorithm (true positive) divided by the

total number of failed firms (true positive plus false negative). Sensitivity alone, without considering the correct recognition rate, cannot be used to evaluate the performance of a classifier since sensitivity does not take into account false-positives (i.e. sound firms that have been classified as failed) (Mallet, Halligan, Thompson, Collins, & Altman, 2012; Trevethan, 2017). For instance, a highly sensitive classifier with a sensitivity of 100% could simply be obtained using a classifier that assigns all firms to the failed category without considering any of the ratios that have been considered in this paper. Such a classifier would be highly sensitive but would be useless since its correct recognition rate (i.e. the proportion of cases that overall have been correctly classified) would be poor since it would classify as failed also all the firms that are healthy.

On the other hand, specificity is the number of firms that have been classified by the algorithm as healthy as a proportion of the total number of firms

that are actually healthy. Specificity alone cannot be used to evaluate the performance of a classifier without considering the correct recognition rate. If a firm tests positive (failed) to a highly specific test than it would have a great probability of being a failed firm, therefore, a highly specific classifier with a good correct recognition rate could be useful as a warning signal.

In a framework where timely detection of a distress situation is of the utmost importance to allow for corrective interventions in order to avoid a negative outcome that can be the bankruptcy of a firm or the death of a patient, a test with high sensitivity is essential since it gives the probability of detecting the disease or the distress status when it is present. In situations when one of the outcomes is an absorbing state (like death or bankruptcy) the two types of error (false positive and false negative) do not have the same importance. It is better to classify a healthy firm or person as sick (false positive) and therefore ask the firm to undergo some unnecessary check than to classify a firm in distress as healthy (false negative) and avoid submitting it to some interventions that could have saved it.

Unbiased estimates (McLachlan, 2004) of these quantities can be obtained via cross-validation. We decided to use a special configuration of cross-validation known as leave one out (loo): in turn, an element is held out and the classifier is trained on the remaining $n-1$ firms and then the classifier is tested on the holdout firm. This is repeated n times, one time for each firm in the data set. This technique is particularly useful in our case since the dataset is not so large and training the algorithm on the largest possible available data is of paramount importance.

The use of an independent test sample to assess the performance of the classifier is not so frequent in the literature related to bankruptcy prediction as it should be. Although in the specialized literature it was suggested the need of an independent sample to test the classifier (Jones, 1987), several papers published have continued to test the performance of various classifiers using only resubstitution error i.e. the error rate that is obtained applying the classifier on the data it has been trained upon.

5. RESULTS

In Table A.1 (see Appendix A) the 95% confidence intervals for the performance parameter (correct recognition, specificity, and sensitivity) for the used algorithm over 300 trials have been displayed. Results have been displayed for an offset up to 8 years prior to failure ("time lag").

As it should be expected, in general, the performance of the classifier tends to worsen as the time lag increases. Confidence intervals that include 0.5 as a possible estimate of the true parameter have been displayed in bold. They do not perform better than a random classifier that assigns classes according to the flip of a balanced coin. The method shows confidence interval up to 7 years prior to failure that does not contain 0.5 and therefore performs better than a random classifier. At 8 years prior to failure, the method tends to show performances that are still far from the random

recognition rate (confidence interval equal to [0.626; 0.865]). In trying to predict the failure of a firm an important performance indicator is sensitivity since it gives the probability of the classifier to detect a firm that is going to fail. High sensitivity is a requirement for all classifiers that should predict the health of a firm since classifying a failing firm as healthy is more costly than classifying a healthy firm as failing. Considering then sensitivity confidence intervals, the picture gets a little less comforting that what it looks like simply considering correct recognition rates. The used method seems to have high specificities that bring up the correct recognition rates. Therefore up to 6 years prior to failure it seems to be possible to predict with fairly high specificities and sensitivities (greater than 0.7) the failure of a SME.

The situation is a bit different when considering profitability indicators instead of financial indicators. The 95% confidence intervals for the average correct recognition rates, specificities, and sensitivities using only profitability ratios, have been reported in the last two columns of Table A.1. Using only profitability ratios the used methodology seems to perform fairly well although the average recognition rate is mainly due to high specificity and the sensitivity 6 years prior to failure is close to the random recognition rate. As previously stated, high sensitivity is mandatory in failure prediction since classifying a failing firm as healthy is more dangerous than classifying a healthy firm as failing.

It is worth noticing that the performance obtained using profitability information is almost always worse than the corresponding obtained using financial ratios, implying that the financial information they carry is more informative to determine if a firm is going to survive or fail. This is probably a result that is characteristic of Italian SMEs.

Therefore it seems that both profitability and financial ratios could facilitate the prediction of a possible situation of distress for a company with a sufficient enough time frame to take action against it (Charitou, Neophytou, & Charalambous, 2004; di Donato & Nieddu, 2015; Charalambakis & Garret, 2019). The used classifier on average seems to provide a recognition rate greater than 0.5 (random recognition rate) considering a time frame of up to 7 years prior to failure. The recognition rate for 8 years does not include the random recognition rate of 0.5 but is dangerously close. Since the dataset is balanced between failed and healthy companies the correct recognition rate is an average of sensitivity and specificity. Since the objective is to predict possible situations of distress, sensitivity is the main objective. With this respect, financial indicators seem to perform better than profitability ones.

Therefore *H1* seems to be verified: the method highlights a fairly acceptable recognition rate up to 6-7 years prior to failure.

Using the financial ratios method seems to work fairly well with acceptable levels of recognition, specificity, and sensitivity.

This does not confirm *H2* since we were expecting a better performance using profitability ratios instead of financial ratios.

From Table A.1 the sensitivity obtained for profitability ratios at various offsets in time is not as

good as it is for financial indicators. The results can be explained considering the characteristics of SMEs in Italy, having personal connections with banks and financial institutions providing them with financial resources without taking into account the economic ratios of the firm and the real capability of the company to generate enough revenues.

It is likely that banks may pay their attention more to the capability of the company in repaying its loans in a short time instead of the actual health of the firm and on its economic situation.

6. CONCLUSION

To test our hypotheses we have performed a cross-sectional study based on a sample of 100 Italian non-listed SMEs which financial and profitability performance has been studied over the period 2000-2011, considering 50 firms that have declared bankruptcy during this time period and 50 still operating on the market over the same period. We have verified that using a nonparametric classification algorithm (Nieddu & Patrizi, 2000), it is possible, considering just financial indicators, to predict with fairly high accuracy (correct recognition, sensitivity, and specificity) the health status of a company.

It means that financial ratios are good in predicting corporate failure. When the failure prediction is based on profitability ratios (see Table A.1) the performances of the classifier get slightly worse.

The results of the analysis can be explained taking into account the characteristics of SMEs in Italy where they have personal connections with banks and financial institutions lending money without considering too much the economic ratios of the firms and the real capability of the companies to survive over time.

In fact, banks only consider the short term period and focus on the capability of these firms in repaying their loans. For this reason, they pay more attention to financial ratios that highlight the ability of the company to satisfy the financial obligations. This is also due to the difficulty for SMEs, because of their limited size and limited resources, to reach good profitability indicators that could prevent them to get any kind of financial fund.

The results obtained are limited and characteristic of the Italian SMEs' framework and its connection with the credit system. They should not be extended to other references.

There are a few more limitations of this study that should be outlined. The sample is quite limited in size and cannot represent the whole of the Italian productive system during the time frame considered. To limit the possible confounding effect of other exogenous variables, a stratified random sample of firms with respect to size and sector has been considered. The limit of the sample can influence the power of the tests that have been carried out so only significant results have been stressed.

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APPENDIX A

Table A.1. Performance on financial indicators and profitability indicators for various offsets

	Time lag (years)	Financial Indicators		Profitability Indicators	
		Estimates		Estimates	
		95%Confidence Interval		95%Confidence Interval	
Correct Recognition	1	0.783	0.914	0.817	0.921
	2	0.856	0.949	0.78	0.888
	3	0.82	0.936	0.789	0.907
	4	0.888	0.962	0.715	0.863
	5	0.813	0.930	0.740	0.871
	6	0.787	0.923	0.686	0.859
	7	0.659	0.879	0.658	0.865
	8	0.626	0.865	0.516	0.797
Sensitivity	1	0.637	0.856	0.749	0.886
	2	0.772	0.912	0.652	0.832
	3	0.710	0.897	0.719	0.863
	4	0.838	0.94	0.603	0.799
	5	0.698	0.885	0.629	0.815
	6	0.708	0.89	0.555	0.801
	7	0.551	0.86	0.620	0.884
	8	0.518	0.863	0.468	0.772
Specificity	1	0.897	1,000	0.857	0.984
	2	0.916	1,000	0.866	0.985
	3	0.898	1,000	0.835	0.976
	4	0.913	1,000	0.793	0.959
	5	0.894	1,000	0.814	0.964
	6	0.828	0.993	0.763	0.969
	7	0.708	0.960	0.626	0.916
	8	0.648	0.954	0.484	0.903