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BUSINESS FAILURE PREDICTION MODELS: FINDING THE CONNECTION BETWEEN THEIR RESULTS AND THE SAMPLING METHOD

Abstract*: Since Beaver's and Altman's pioneering work, business failure prediction has become an important topic in corporate finance literature. Most of the developed models have achieved good prediction results, but they have used a paired sample of failed and non-failed firms, which is not representative of the population from which it is chosen.*

This paper focuses on the development of both failure prediction models on a paired sample and a random sample of firms with head offices located in the region of Castilla y León (Spain), in order to prove if the predictive power of the models is affected by the sampling method.

To estimate both models, we apply a logistic regression analysis where we consider a set of financial ratios as independent variables, which is first reduced through the application of a principal components analysis. The results show there are differences both in the significant variables and in the classification results, which are not so high in the random sample as in the paired one, especially with regard to failed firms.

Keywords: *business failure, financial ratios, sampling, principal components analysis, logistic regression, prediction, Spain.*

JEL classification: C35, C53, C83, G33.

1. Introduction

Business failure prediction is an important research field in corporate finance literature, which has become topical in recent times, due to the serious economic and financial crisis which is affecting many countries in Europe and all over the world.

The origin of the development of business failure prediction models is placed in Beaver's and Altman's work, which is considered to be pioneering in this field.

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Using their models as a basis, a large list of researchers has developed their own ones, using a wide range of financial ratios as independent variables in statistical models obtained by a variety of methodologies, in order to predict failure.

Beaver (1966) carried out his study from a univariate viewpoint. Despite its importance as a starting point for this research field, it has the disadvantage of not considering the possible relations between variables. That is the reason why Altman (1968) complemented Beaver's work, in the sense of applying a multivariate analysis, specifically discriminant analysis.

This methodology has been used in a long list of studies published during the seventies and eighties, both in the United States (Deakin 1972, Edmister 1972, Blum 1975, Elam 1975), and in other European countries. It was towards the end of the seventies when the research about business failure started in the United Kingdom, the first country in Europe in developing this line, where the most outstanding researcher is Taffler (1982). Other countries where an important research stream was developed during the eighties and the beginning of the nineties are Spain (Laffarga *et al*. 1985) and Finland (Laitinen 1991).

In spite of its broad application, discriminant analysis has some drawbacks regarding its assumptions, so research about failure prediction evolved to other less demanding statistical methodologies. Thus, in the eighties Ohlson (1980) and Zmjiewski (1984) pioneered the application of logit and probit analysis, respectively, in the prediction of business failure. But the use of this set of methodologies was not limited to American studies, and the work was increased by British (Peel *et al*. 1986), Finnish (Laitinen & Laitinen 1998) and Spanish (Pina 1989) researchers, as it had happened with the application of discriminant analysis. As well as these countries, in the 1990s the Greek began an important school of research about failure prediction (Theodossiou 1991).

During the nineties and in the first decade of the twenty-first century, statistical methods, especially discriminant analysis and logistic regression, has gone on being applied in order to predict failure. However, due to the advances in computer science, new techniques from artificial intelligence field have been introduced in the prediction of business failure, such as neural networks (Odom & Sharda 1992), and rough set methodology (Slowinski & Zopounidis 1995). Moreover, as artificial intelligence methodology seems to lack a statistical basis, a research line consisting of a comparison between those methods and the traditional statistical ones has been developed (Altman *et al*. 1994, Dimitras *et al*. 1999, Charitou *et al*. 2004).

A common figure of most previous studies is the use of a paired sample constituted by the same number of failed and non-failed firms. Nevertheless, this kind of sample has the drawback of not being representative of the population from which it is chosen, since this sampling method does not respect the population proportions in the sample. For this reason, the good prediction results achieved by these models have drawn some criticism.

The aim of this paper is to prove whether the predictive power of the previously developed models is due to the kind of sample they have used, so we select both a paired and a random sample of small and medium-sized firms with head offices in the region of Castilla y León (Spain). Each sample is used to develop a business failure model by the application of a logistic regression analysis, in order to identify the variables that best explain and predict failure in the two samples.

In order to reach our target, the paper is organized as follows: The next section is a description of the sampling design, which first involves the definition of what business failure is. In Section 3 we are dealing with the financial ratios that help explain and predict that event and the selection of the most important variables by a Principal Components Analysis (PCA). Section 4 introduces and discusses the prediction results in both samples. The paper concludes with the summarizing remarks.

2. Firms sample

The first step forward in the development of a business failure prediction model is the selection of the firms sample aim of the study.

Provided the main target of a failure prediction model is to set what variables best discriminate between failed and non-failed firms, it is necessary to include both groups of firms in the selected sample. Therefore, the first decision to make is about what is it understood by failure.

Once the criterion event for business failure is decided, it is possible to identify failed and non-failed firms in the population, so as to select some of them to be part of the two kinds of samples. In order to do that, we follow the sampling design which is next described.

2.1. Definition of business failure

One of the difficulties arisen when obtaining a business failure prediction model is to define what this event is. That is because a business failure includes a variety of situations with a negative influence on firms' activity that can cause their final disappearance. And there is also a diversity of parties involved in a firm (investors, lenders and suppliers, clients, employees, managers or auditors), for whom the consequences of the firm disappearance are different.

All these groups are potential users of any prediction model and, as the firm failure has different effects on them, they also seek a different applicability when they use the model in order to predict business failure. Therefore, the event used as a definition of this situation should also be different. Actually, a revision of the previous literature in this field beginning by the referred works shows different definitions of failure, depending on the aim of the respective model: a firm's formal declaration of bankruptcy or another legal proceeding (Altman 1968, Taffler 1982, Laffarga *et al*. 1985, Ohlson 1980, Zmijewski 1984, Peel *et al*. 1986, Pina 1989, Theodossiou 1991, Odom & Sharda 1992, Dimitras *et al*. 1994, Charitou *et al*. 2004); failure in the sense of insolvency, as the inability of a firm to pay debts as they fall due (Edmister 1972, Laitinen 1991); or a group of different situations, as well as the two previous ones (Altman *et al*. 1994, Laitinen & Laitinen 1998), such as a bond default, an overdrawn account and the nonpayment of a preferred stock dividend (Beaver 1966, Deakin 1972) or an explicit agreement with creditors to reduce debts (Blum 1974, Elam 1975).

As it can be observed, the majority of developed models have used a juridical definition of failure, either bankruptcy or liquidation or whatever other used concepts, attending the current legislation in each country. Although some drawbacks can be linked to each of the mentioned definitions, since they depend on the prediction model user's interests, bankruptcy as a surrogate for business failure has the advantage of being a highly visible legal event that can be objectively dated (Keasey & Watson 1991). Furthermore, most models contain financial ratios as independent variables to predict failure, so this definition would avoid the problems involved by the fact that both predictor variables and the event they try to predict are based on the same financial statement when a more economic criterion, such as income level or liquidity position, is used (Jones 1987).

For all these reasons, we also consider a legal definition of failure, as the firm's formal declaration of one of the three possible proceedings in the Spanish law, which are included under the general terminology of bankruptcy.

2.2 Sampling design

Taken into account the legal definition for business failure, we proceeded to develop the sampling procedure.

As it was mentioned before, the most common sampling method has been to derive the sample of failed firms and next to select the same number of non-failed firms by matching them to the failed ones devoted to the same industry and being of the same size. This state-based sample (Zmijewski 1984) has the advantage of assuring a big enough number of failed firms, since there is a low frequency rate of failing firms in the economy.

Nevertheless, that is precisely one of the criticisms to this non-random sampling method, which does not respect the population proportions in the sample. Furthermore, classical statistical methods used in failure prediction models are based on the assumption of a random sampling design (Balcaen & Ooghe 2006). As a result, parameter estimates are inconsistent and biased, which leads to an overstatement of the model's ability to predict (Palepu 1986), as the misclassification error rate for the failed firms is understated (Balcaen & Ooghe 2006).

In order to prove these statements, we decided to compare both sampling –matching and random– methods regarding prediction results.

First of all, we identified the firms' population in the database SABI, used to collect the information, with the requirement of availability of financial statements for three consecutive economic years.

Considering our criterion for business failure, there were 59 failed firms, all of which were chosen to be part of the failed group in both samples, due to the low failure rate in the population (41,584 companies altogether).

Regarding the non-failed firms, the database included a total of 41,525 companies. For the random sample, using the formulae appropriate to calculate the size for this group, it resulted in a sample size of 396 firms. These firms were selected from the same industry in which failed companies developed its activity, attending each industry population size, so as to respect characteristics and peculiarities of different industries. A summary of the study random sample can be observed in table 1.

Table 1. Firms' random sample

INDUSTRY		FAILED FIRMS		NON-FAILED FIRMS	
Activity	**CNAE–93 Code**	**Number**	**Percentage**	**Number**	**Percentage**
Agriculture	01	5	8.5	14	3.55
Manufacturing	14	2	3.4	4	1
	15	6	10	16	4
	17	1	1.7	1	0.25
	18	1	1.7	3	0.75
	20	2	3.4	8	2
	22	1	1.7	5	1.25
	24	2	3.4	2	0.5
	26	2	3.4	5	1.25
	28	1	1.7	9	2.3
	30	1	1.7	1	0.25
	34	1	1.7	1	0.25
	36	2	3.4	4	1
Building	45	12	20.3	85	21.5
Service	50	1	1.7	24	6.1
	51	4	6.8	50	12.6
	52	7	11.9	40	10.1
	55	1	1.7	28	7.1
	63	1	1.7	6	1.5
	70	2	3.4	48	12.1
	74	2	3.4	30	7.6
	80	1	1.7	5	1.25
	85	1	1.7	7	1.8
	Total	**59**	**100**	**396**	**100**

To derive the paired sample, each of the 59 failed firms was matched with a non-failed one randomly selected from the same industry, resulting in a total sample size of 108 companies.

3. Explanatory variables of business failure

In order to obtain a business failure prediction model, it is necessary to consider a set of variables that explain that event and, therefore, are supposed to contribute to the prediction of business failure.

Obviously, a firm's failure mainly depends on the activity it develops, which is reflected in the information published in its financial statements. As an easier way of treating all this information, it is usual to compute financial ratios relating different accounting entries. That is the reason why most models have included a variety of financial ratios which best describe the firm's activity as independent variables to predict failure.

Nevertheless, due to the lack of a theory of financial distress, the selection of financial ratios by researchers has been basically empirical, which has resulted in a huge list of ratios potentially explanatory of business failure.

In an attempt to reduce that large list, before estimating the prediction models in both samples, we first apply a Principal Components Analysis (PCA), in order to focus on those ratios with the highest explanatory power about the event of interest.

3.1 Financial ratios

Provided the information extracted from financial statements reflects the firm's activity and that is the main factor influencing on its possible failure in the future, independent variables included in the developed prediction models have consisted in financial ratios, which measure different issues of the business activity.

Even though the choice of ratios should be based on an economic theory of the relationships between the failure process and variables potentially explanatory, the selection has been basically empirical. That means that researchers have selected the financial ratios for their studies on the basis of their popularity in literature and their predictive success in previous research as independent variables to predict failure, as Beaver (1966) did.

These criteria have also been taken into account in order to select the financial ratios for our study, but we have limited to those ratios that have been used (and became significant) in several of the previously developed models and especially those of Beaver (1966) and Altman (1968), so as to reduce the large list of financial ratios to be potentially considered.

A last criterion taken into consideration to make the final selection of financial ratios has been the information availability for the firms in our sample, since the selected ratios are computed in the three-year period of study. Actually, information regarding the financial ratios was collected for a three-year period before failure, in the case of failed firms, and the last three years of activity for the non-failed ones.

Table 2 shows the final list of 27 chosen financial ratios, classified in six categories, together with their respective definition.

Table 2. Financial ratios used as independent variables

Category	Name	Definition
Liquidity	CACL	Current ratio: Current assets / Current liabilities
	AT	Acid test: (Current assets – Inventories) / Current liabilities
	CCL	Quick ratio: Cash / Current liabilities
	WCTA	Working capital / Total assets
	WCE	Working capital / Equity
Profitability	ROA	Return on assets: Net income / Total assets
	ROE	Return on equity: Net income / Equity
	EBTE	Earnings before taxes / Equity

	EBTTA	Earnings before taxes / Total assets
Leverage and solvency	TLTA	Total liabilities / Total assets
	CLTA	Current liabilities / Total assets
	FLTA	Fixed liabilities / Total assets
	ETA	Equity / Total assets
	ECL	Equity / Current liabilities
	EFLFA	(Equity + Fixed liabilities) / Fixed assets
	ORFE	Operating result / Financial expenses
	FES	Financial expenses / Sales
Turnover and activity	STA	Sales / Total assets
	Var(SALES)	$Sales_t$ / $Sales_{t-1}$
	WCS	Working capital / Sales
	CAOI	Current assets / Operating income
Cash-flow	CFTA	Cash flow / Total assets
	CFTL	Cash flow / Total liabilities
	CFCL	Cash flow / Current liabilities
Economic structure	CATA	Current assets / Total assets
	FATA	Fixed assets / Total assets
	CTA	Cash / Total assets

3.2 Selection of variables: Principal Components Analysis (PCA)

A last step with regard to the selection of variables to be considered in the prediction models is the application of a Principal Components Analysis (PCA), whose aim is the reduction of the large list of financial ratios to a smaller number of factors with a high explanatory power of business failure.

In each sample, PCA was applied on the initial list of 27 financial ratios, referred to the last year of the study period. Those ratios which did not correlate with any of the obtained factors were deleted in successive steps. Moreover, to increase the variance percentage explained by the factors, ratios containing redundant information were also removed from the analysis. The whole process was made with the statistical software SPAD 6.0.

Six factors were finally extracted in both samples. In the random one, these factors explained 85.02% of the original information expressed by the 27 financial ratios, while in the paired sample the percentage of explained variance was 73.36%.

Out of the 27 financial ratios, 15 ratios in the random sample and to 20 ratios in the paired one were highly correlated with the different factors. These correlations between factors and ratios allow us to provide a description to the different factors, as it is shown in table 3.

Table 3. Factors from PCA and related variables

SAMPLE	
Random	**Paired**
Liquidity (CACL CCL AT)	Liquidity (CACL CCL AT)
Liability structure (ETA CFTA CLTA)	Liability structure (ETA CFTA CLTA)
Economic profitability (ROA)	Economic profitability (ROA)
Cash-Flow (CFTL CFCL)	Cash-Flow (CFTL CFCL)
Current position (CATA)	Current position (CATA)
Turnover (FES WCS)	Equity (ROE WCE)
	Working capital (WCTA WCS WCE)

Some factors are common to both samples: they describe liquidity issues, liability structure, economic profitability, cash-flow and current position of the firms in each sample.

However, there are also some differences. In the random sample, a specific factor describing turnover is identified, since it is correlated to the ratios of financial expenses (FES) and working capital (WCS) on sales. In the paired sample, two important factors are extracted, measuring equity and working capital issues.

4. Prediction Results

In order to predict the failure of the firms in both samples, a logistic regression analysis was applied, provided it is one of the most used statistical methods in this field and has the advantage of not demanding any previous statistical requirement regarding its application, as discriminant analysis does.

As far as the models estimation is concerned, the ratios correlated with the six extracted factors by PCA were considered as independent variables to enter in the models. In order to avoid the drawback of obtaining a model for each year of the three-year period of study, we decided to include the variables measured in the three years. Statistical software SPSS 19 was used to obtain the different models.

The results for the random sample are shown in table 4. According to the likelihood ratio test used for variable selection, eight ratios entered the model, although the Wald statistic for ROA is not significant. The other significant variables are the percentage of current assets (CATA) and working capital on assets (WCTA) and the cash-flow on total debt (CFTL) the last year before failure, as well as the quick ratio for this year (CCL) and the third one before (CCL_2) and two ratios measured the previous year: the proportion of equity (ETA_1) and cash-flow (CFTA_1) on total assets.

Table 4. Logistic regression model (Random sample)

Variable	Coefficient	Wald test	*p*-value	Odds ratio	Odds ratio 95% confidence interval	
					Lower	Upper
CCL_2	–5.162	7.403	0.007	0.006	0.000	0.236
ROA	0.003	0.476	0.490	1.003	0.995	1.010
CCL	–5.658	5.302	0.021	0.003	0.000	0.431
CATA	0.093	14.131	0.000	1.097	1.045	1.152
ETA_1	0.029	7.963	0.005	1.029	1.009	1.050
WCTA	–10.380	17.209	0.000	0.000	0.000	0.004
CFTA_1	–8.830	8.473	0.004	0.000	0.000	0.056
CFTL	–7.995	12.668	0.000	0.000	0.000	0.028
Constant	–1.065	2.783	0.095	0.345	–	–

As it can be observed, significant variables basically measure different liquidity and current issues, as well as the ability of the firm to generate resources internally. Moreover, all the variables, except CATA and ETA_1, have a positive influence on failure, in that an increase in their value involves a reduction on the odds ratio for the failure probability.

Table 5. Logistic regression model (Paired sample)

Variable	Coefficient	Wald test	*p*-value	Odds ratio	Odds ratio 95% confidence interval	
					Lower	Upper
ETA	–0.042	5.117	0.024	0.959	0.925	0.994
CTA_2	–15.915	8.729	0.003	0.000	0.000	0.005
WCE	–0.223	6.190	0.013	0.800	0.671	0.954
ROE	–0.011	7.274	0.007	0.989	0.981	0.997
CFTL_1	–12.082	5.128	0.024	0.000	0.000	0.197
FES	0.157	3.499	0.061	1.170	0.993	1.379
Constant	3.377	10.997	0.001	29.280	–	–

In the paired sample, the number of variables entering the model is six, because of their significance in explaining and predicting business failure, as the *p*-value for each ratio in table 5 shows. However, the turnover of financial expenses (FES) is only significant at a 10% level. Actually, the confidence interval estimated at a 95% level for the odds ratio corresponding to this variable includes the null value (one), which means that it has no influence on failure probability.

The rest of variables are the proportion of equity on total assets (ETA), the percentage of working capital (WCE) ant the return (ROE) on equity, measured in the last year before failure, as well as the proportion of cash-flow on total debt (CFTL_1) the second year before failure, and the percentage of cash on total assets referred to the third year before failure (CTA_2). Although these two last variables are significant in the model, it can be observed that some issues related to equity are important in this sample in order to avoid failure. In any case, for all of them the odds ratio (and the respective confidence interval) is less than one, involving a positive influence on business failure.

Taking into account the significant financial ratios in the two logistic models, each firm in both samples was classified in one of the two groups according to the failure probability and the classification results are shown in table 6.

Table 6. Classification results

Firms	Sample	
	Random	**Paired**
Failed	43.48%	91.11%
Non-failed	99.59%	75%
Total	**90.69%**	**83.95%**

The total hit rate is quite similar in both samples, although slightly higher in the random one, since nearly 91% of the firms in this sample are correctly classified, opposite to 84% of the firms in the paired sample. Therefore, the different composition of firms belonging to each group in the two samples does not have a large influence on the total classification results.

Nevertheless, some differences regarding the classification in each group can be observed. On the one hand, the correct classification percentage for the non-failed firms group, when considering a paired sample, has slightly decreased, but it remains quite high. On the other hand, the percentage corresponding to the failed firms in that sample has double its figure. This large improvement in the hit rate for failed firms is due to the increase in the proportion of this kind of companies in the sample (50%), which makes easier to achieve a better classification for them, as there is only a 13% of failed firms in the random sample.

In conclusion and according to the previous results, it can be deduced that the use of a paired sample, in comparison with a random one, seems to overestimate the predictive ability of business failure models.

5. Conclusions

Since Beaver’s and Altman´s pioneering studies, different statistical methods, such as discriminant analysis and logistic regression, have shown their ability to predict business failure in samples corresponding to different periods and countries.

Nevertheless, some of these studies, which have used a paired sample of failed and non-failed firms to obtain their models, have drawn criticism for basing their prediction results in a sample that is not representative of the population from which it is derived, involving invalid results.

In an attempt to empirically prove this statement and with a comparative aim, a random and a paired sample of firms belonging to the SME sector in the region of Castilla y León (Spain) were selected in order to develop both failure prediction models, which include financial ratios as independent variables to predict failure.

Before estimating the prediction models through the application of a logistic regression analysis, a principal components analysis was applied, in order to reduce the number of financial ratios as potentially explanatory variables in each model. In both samples six factors were extracted, some of which were common to the two samples, such as liquidity, liability structure, economic profitability, cash-flow, and current position. Apart from the latter, some specific factors to each sample were identified: in the random sample, a turnover factor, and in the paired one, two factors describing equity and working capital.

The financial ratios correlated to the extracted factors were considered as independent variables to enter in the prediction models, where some differences were observed. In the random sample, the most relevant issues in order to avoid a firm's failure are liquidity and resources generation, which are also significant in the paired sample, but issues related to equity play an important role in eluding that event in this sample.

Apart from these differences in the prediction models and according to the aim of this paper, the most outstanding differences are observed in the classification results. As it was supposed, the sample composition has influence on the percentage of correctly classified firms in each sample. The percentage for the failed firms seems to be higher when a paired sample is used, since it increases the proportion of these firms in the sample, while the percentage corresponding to the non-failed firms group, which has slightly decreased, remains quite high.

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