“Syndromes Leading to Failure: An Exploratory Research”

SYNDROMES LEADING TO FAILURE: AN EXPLORATORY RESEARCH

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Abstract

Prediction of corporate failure research typically focused on the design of multivariate prediction models for the discrimination between failed and non-failed firms. This research attracted some criticism due to the inability to formulate generally applicable models. Several reasons may have led to the impossibility of formulating such models: it has been argued that firms suffering financial distress may have incentives to manipulate accounting information in order to increase users' confidence; statistical techniques could over-adjust prediction models; and finally, the existence of different failure processes is not considered by prior research.

The main objective of the present research is to investigate the unique characteristics of failed companies, the reasons for each particular failure and the presence of different failure processes.

The present study aims to be the first step in the opening of a new stage in the development of a theoretical framework on corporate failure. It is assumed that there exist different paths to failure, instead of a simple differentiation between healthy and failed firms. This is the main contribution of the paper, which is relevant to both researchers and practitioners. It opens up new possibilities for future research, following new experimental designs. For practitioners, it constitutes a new framework for the development of decision-aid tools (raising the opportunity to use decision making systems based on different rules or models for different paths).

Key words: Corporate failure, syndromes, quality of financial information.
JEL classification: G33, G11, M41.

Previous evidence and research objectives

In 1968, Altman published his well known Z-score, which measures the proximity of a firm to corporate failure. Z-score is a lineal multivariate model, constructed by using the statistical differences observed between organizations belonging to two different samples (failed vs. non-failed) and paired by size and sector. Z-score neither explains why some firms fail nor replicates the analysts' decision process, but increases the efficiency of the analysis effort by reducing the time devoted to analyze firms with very high or very low failure probabilities and thus increasing the time devoted to those in the "grey zone".

During the following 30 years, this experimental design was applied to other periods, industries and countries, using similar, or slightly different, statistical tools, variables, time horizons and sample designs – literature reviews can be found in Altman (1983), Zavgren (1983), Jones (1987), Dimitras et al. (1996), Altman & Narayanan (1997), Laitinen & Kankaanpää (1999) and Balcaen and Ooghe (2006). The experimental design and the instrumental focus remained unchanged throughout. Systematically, samples of failed and non-failed firms were compared, and those models that could achieve a classificatory success comparable to that obtained by Altman (1968) were labeled as good models. Discriminant variables and model selection were considered empirical questions that should be solved by choosing those with higher classificatory success (Jones, 1987; Bartley & Boardman, 1990). The expected benefits justified the use of inappropriate statistical tools, data mining or the lack of interest in the development of a general theory of corporate failure (Joy & Tollefson, 1975; Pinches, 1980; Belkaoui, 1980; Zmijewsky, 1984; Piesse & Wood, 1992; Charitou et al., 2004; Diaz Martínez et al., 2005).

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However, the criticism of the typical experimental design was not caused by any of the reasons stated above, but from its inability to develop generally applicable models that could provide adequate rates of success in samples that were different from those used in their formulation (Begley et al., 1996; Sung et al., 1999; Grice & Dugan, 2001). Under these circumstances the instrumental objective may not be reached, due to the risk associated with the use of the models in decisions that only admit low error rates. At this stage, the absence of an underlying theory and the impossibility to formulate generally accepted decision rules due to the difficult interpretation of the results, contributed to the crisis of those models. As Balcaen and Ooghe (2006, 87) suggest, the definition of failure itself is arbitrary, and "*may result in models with misleading classification power and weak predictive usefulness in practice*".

Different factors might explain the instability of the models and the reduction of their predictive accuracy. It has been argued that firms facing financial tensions or situations close to failure have incentives to manipulate financial accounting information to increase user confidence (Beaver, 1968; Beneish, 1997; Rosner, 2003). Another explanation is that statistical techniques over-adjust predictive models in order to reach the maximum classificatory success within the sample, but reduce the external validity of the models. The pursuit for the maximization of predictive success encouraged researchers to systematically contrast the predictive ability of a wide range of variables and models, usually without the appropriate theoretical support. Under such circumstances, it is presumable that the selected model could be significantly influenced by spurious statistic relationships, present in the concrete sample of firms used (Zavgren, 1983; Hair et al., 1999). Finally, Laitinen (1991), states that many of the errors on the predictive models are originated by the incorrect hypothesis, underlying the experimental design, that there is a unique process that leads to failure.

In order to overcome the stated limitations, the main objective of the present paper is to propose a first step towards the development of a new theoretical framework of corporate failure, identifying different processes, paths or syndromes of failure.

By investigating the characteristics and the financial situation of failing firms and the factors affecting each particular failure, the existence of different process driving to failure is inferred. A formal taxonomy and rules to classify firms into each category are developed. Finally, a confirmatory statistical analysis is performed.

A proper identification of different processes, paths or syndromes of failure might open promising avenues for research by means of the development of a new theoretical framework. The consideration of those syndromes offers a range of opportunities for future research and for the subsequent development of decision aid tools.

The structure of the paper is as follows. The next section is devoted to present the sample selection procedure. The main objective of the paper is approached in the following section, where the grouping of the cases and the resulting syndromes are presented. The paper ends with a confirmatory analysis and the conclusions section.

Sample selection

The sample of failed[1] firms was obtained from the data bases *SABI* (database comprising financial statements for a wide range of firms) and *Baratz* (database including summaries of press news). Financial firms were excluded from the analysis, due to their special characteristics. In order to be included in the sample, firms were required to have relevant liabilities and sufficient size to disclose standard and audited financial statements. To obtain a relevant and valid sample the following conditions were required:

1) The bankruptcy petition should have been filed, at least, two years before the empirical study was performed. This requirement allowed identifying a reliable sample of non-failed firms as control group. The date of the bankruptcy protection filing was obtained from *Baratz*.

[1] A firm was considered failed when a bankruptcy petition or a repayment plan is presented, using a juridical definition of failure.

2) Accounting data for the 3 periods before filing should be available. We considered that the accounts had been released before filing if the financial statements were presented at least six months earlier. Accounting data were obtained from *SABI*, public register offices and Spanish Securities and Exchange Commission (CNMV) database.
3) Financial Statements of those 3 years should have been audited (data obtained from *SABI* or from the public register offices).
4) There should not be previous filings, bankruptcies or interruptions of the activity of the selected firms before the one under control (information: *Baratz* or audit reports). This constraint tried to avoid corruption in the sample.
5) At the time of the filing date, or at least at the end of the preceding year, recognized liabilities should be relevant (we stated a minimum limit of 6 million €).

These restrictions were met by 46 firms. From this initial sample, 5 firms were rejected, due to adverse audit opinions (the financial statements did not present a true and fair view) in, at least, two years. In consequence, the sample was composed of 41 failed firms that filed for bankruptcy protection. The total amount of liabilities of the filings was 1.252 millions €. The average of liabilities was 31 millions €. The minimum limit for liabilities was 6 millions € and the maximum was 144 millions €.

For each failed firm, a comparable healthy company was chosen, taking into account the following restrictions and conditions:

a) Same industry, measured by the first four digits of the Spanish Classification of Economic Activities (CNAE93).
b) Similar size, measured by total assets and net sales.
c) Annual accounts should be audited without qualifications in any year of the sample period.
d) All accounting data for all the years in the sample period should be available.
e) There should be no evidence of later filings for the control firms (confirmed with SABI and Baratz news until four years after).

The control sample consisted of 40 non-failed firms that fulfilled all these conditions. Only for one failed firm it was impossible to find a "partner" that met the requirement of unqualified audit report for all the period.

Grouping Cases: syndromes

One of the major reasons that may have led to the impossibility of formulating generally applicable models is the potential existence of different failure processes (syndromes). As Balcaen and Ooghe (2006, 78-79) indicate, the classic failure prediction models do not treat company failure as a process, which results in serious consequences as "*the relative importance of the variables and the ex-ante predictive accuracy of the model will be implicitly determined by the frequency of occurrence of the different phases of the failure process and the different kinds of failure paths in the estimation sample of failing firms*". In this line, our main aim is to identify failure paths or syndromes for failed firms.

As theoretical starting point for such analysis, the model suggested by Beaver (1966), slightly modified, was used. We considered that the financial failure occurs when the debtor is unable to meet the financial obligations. Given that any creditor would defer the collecting of the debt (or to lend more funds) if he/she is sufficiently compensated for it and if there are enough warranties of recovery, it could be argued that a firm would not fail if the external agents do rely in the firm capacity to meet its financial compromises in the future. Even, if some of the creditors preferred to cancel their credits, the existence of other agents relying on the firm opens the possibility to borrow the funds from those agents. Favorable prospects would not only increase leverage capacity, but would also attract new investors. Therefore, financial failure occurs when the reliance of the creditors deteriorates.

In our opinion, this confidence is based upon:

(i) Net equity: the difference "real assets less liabilities" is the last warranty for the creditors. Losses expectations diminish this guarantee.

(ii) Expected fund flows, leverage capability and non-operating assets, which are the resources that could be used to meet financial compromises.

The analysis of failed firms rests on the former hypothesis. In order to identify failure processes, an individual financial analysis of each case (failed firm) was performed.

For each case, a set of variables was calculated for a period comprising three years before failure. These variables included information about profitability, leverage, debt coverage, etc. The next step consisted of an individual analysis of each case, developed by a team of researchers with an appropriate degree of expertise in financial analysis. The outcome of the process resulted in a set of reports. Those reports described the actual situation and the previous development of the firm, highlighting the appropriate variables traditionally used in financial analysis and those that displayed relevant variations in the periods prior to failure.

The analysts, following a modus operandi similar to that used in medical diagnosis, looked for the symptoms that could explain the development of the firm and could discriminate one "disease" from another. The advantage of such procedure, particularly when there is no prior knowledge of the syndromes, is that allows paying attention to nuances that could be ignored by statistical tools such as cluster analysis. As no prior theory exists in order to define the syndromes, the potential risk of losing objectivity is compensated by the relevance of the results obtained, that could not be achieved by using statistical tools.

The analysis of the reports confirmed that failed firms did not seem to be in similar situations neither followed a unique process to failure. For a considerable percentage of firms (close to 50%) the failure could be predicted by using the most usual ratios. The vast majority of these firms obtained negative fund flows that resulted in negative, or very low, net equity.

The failure for the rest of the sample did not follow the same path. A second analysis was performed paying attention (and systematically comparing) more specific variables, such as margin evolution, operating turnover & days, relevant expenses and revenues, liquidity and operating ratios, etc. After a detailed examination of the cases, it could be observed that a considerable group of firms (12 cases) presented a sudden degradation of debt coverage variables after a period of significant investments (growth in assets) financed with debt.

The rest of the cases seemed to respond to different circumstances. A small group of firms had a relatively stable position, although the profitability and times-interest-earned ratios showed low values.

Once the different groups were broadly identified, more detailed rules of thumb were developed in order to allow the adscription of the failed firms to each syndrome. The strict application of the rules of thumb resulted in the immediate classification of two thirds of the cases in very homogeneous sets. The resulting classification consisted of 3 categories, labeled and described as follows:

– <u>Black hole</u> (12 cases, 30%). These firms present negative fund flows from operations for, at least, 2 years before failing. In the last year, the equity becomes very low, even negative. Ordinary losses clearly diminish the net equity guarantee. However, net equity does not always show a decreasing trend, since it is usual that those firms issue new capital, adjust asset values, or try to raise extraordinary revenues. Nevertheless, all those resources are quickly absorbed by ordinary losses.

Years before the failing date, those firms present a very weak financial situation. The persistence of this weakness should have been understood, by investors and creditors, as a signal of a high risk of failure. Notwithstanding, new funds are invested in those firms in the years before failure. In our opinion, these firms can be detected and must be avoided.

– <u>Failed growth</u> (10 cases, 25%). These firms exhibit appreciable assets growth in the last years (annual average higher that 10%). This growth is financed through substantial increases in debt. Funds flows from operations, however, do not grow and, at the end, do fall to a level below the starting point. Consequently, interest and debt coverage worsen significantly, and firms are unable to meet their financial obligations. Unlike "black hole" firms funds flows and earnings are usually positive in the three years before failing.

It is difficult to detect the probability of failure of such firms far in advance since deterioration of financial situation is only evident one or, at most, two years before failing. In our opinion, the only symptom of the risk undertaken by these firms rests on their rapid size increase. Under such circumstances, decision makers should (I) give a detailed attention to the development of firms with excessively rapid size increases financed with debt, (II) diversify investments in growth firms, and/or (III) raise the risk premium for this kind of firms.

– Setback (4 cases, 10%). Firms in this group have low profitability (return on assets is never higher than 2 percentage points over average interest rate) and debt/interest coverage is very low. In the last period they suffer relevant losses that consume the retained earnings and drive fund flows to negative. Setback firms usually have positive earnings until the year before the failing date, like failed growth firms. The difference comes from the absence of assets growth and from a weaker departure situation.

Failure probability for those firms was easily sensed several years before failing, due to low interest and debt coverage. However, it is difficult to anticipate the definite date of failure because it is usual for these firms to generate positive earnings and to show relatively stable figures that do not seem to point to degradation in the financial situation. In situations like these, decision makers should avoid firms with low interest/debt coverage, at least when these indicators do not reveal a favorable trend.

There were 15 firms (one third of the sample) that did not conform strictly to all the required rules to be classified into the former categories. Nevertheless, none of them evidenced behaviors that were against our theory of failure. Out of them:

- 7 exhibited very similar features to those of the categorized firms; although they did not comply with one of the characteristics necessary to be included (4 were similar to black hole, 2 to failed growth and 1 to setback).
- 4 were hardly profitable (return on assets was lower than average interest rate and/or was rapidly and gradually diminishing) and unable to meet their financial compromises and new investments.
- 2 were highly leveraged (equity almost non-existent); ordinary losses in any period and/or creditors refusal to renew financial support led them to failure.
- Finally, one had a highly negative equity several years before failing date and other suffered strong losses, from which it could not recover.

Regarding the audit reports, it is interesting to note that 83% of going concern qualifications were found in the reports of black hole or similar firms. This is quite relevant given that those firms only represent 40% of failed firms.

Empirical confirmation

In this section, our aim is to confirm the validity of the proposed classification by using statistical tests. Nominal regressions (multilogit) were found to be the most appropriate technique. This tool is useful to classify cases, based on several variables, into more than one category when those categories are not ordinal. In the present case there were 4 categories: healthy firms and 3 syndromes. The output is a set of n-1 models, over a total of n categories, where each model estimates the probability of a case to be included in the category.

In previous research that estimates classical statistical prediction models the variable selection is usually empirically based, lacking theoretical foundation and therefore preventing for a better selection (Balcaen and Ooghe, 2006). In the current research, we undertake an attempt to overcome this limitation since the theoretical definition of the syndromes allows a theoretically based variable selection. Therefore, the set of independent variables was obtained taking into account the theoretical definition of each syndrome.

In order to avoid multicollinearity problems, a previous correlation analysis was performed. From the results of this test, those variables with redundant information content were filtered. The set of variables finally used was:

R23 Equity/Total Assets

R29C (Negotiated Total Financing + Other Financing (with no explicit cost) – Non-Operating Assets)/Funds Flows From Operations

R30 Earnings before Interest & Tax/Interest Expenses

R39 Return on Assets

T01 Assets Growth

T03 Operating Revenue Growth

For failed firms, the data used were obtained by adjusting the variables by the audit qualifications[1].

The first model included all the firm-year observations in a panel data. Initially, there were another two possibilities: (I) to perform 3 models, one for each distance to failure, and (II) to introduce distance as another independent variable. Given that the date of failure is unknown in advance for the decision maker, it is unrealistic to use distance as a variable because it introduces information in the model that is obviously not available. Therefore, both alternatives were dismissed.

A summary of the general model and its goodness of fit are given in Table 1.

Table 1

General model

Category	*N*		*Goodness of fit*	*Pseudo R^2*
B. Hole	30		Chi^2 302.91	Cox & Snell 80.7%
F. Growth	30			
Setback	11			
Healthy	113		Sig. 0.0000	Nagelkerke 86.1%
N.	184			

In general terms, the model is highly significant (Chi^2 sig.<1%), obtaining high pseudo R^2 values. Table 2 presents the 3 models (n-1). Each model presents the probability of a case to be labeled in the category associated to that model. Those models are not mutually exclusive; therefore, more than one model could show probabilities over 50% for a concrete case.

Table 2

Multilogit model

Groupings (n-1)	*Variables*	*B*	*Typical Error*	*Wald*	*Sig.*
B. Hole	T01	-0.368	1.623	0.051	0.821
	T03	0.807	0.954	0.717	0.397
	R23	-7.661	2.198	12.151	0.000
	R29C	0.010	0.008	1.547	0.214
	R30	-0.235	0.116	4.077	0.043
	R39	-9.282	7.044	1.736	0.188
F. Growth	T01	2.317	1.152	4.047	0.044
	T03	0.460	0.912	0.255	0.614
	R23	-5.413	1.489	13.220	0.000
	R29C	0.008	0.008	1.020	0.312
	R30	-0.060	0.043	1.982	0.159
	R39	-3.164	4.895	0.418	0.518

[1] Previous research indicates that the reliability of the accounting data used to calculate failure prediction models should be a major concern. For instance, results in Abad et al. (2003) indicate that audit reports are able to quantify manipulations on accounting information in close to 20% of the financial statements of firms suffering financial distress. In those firms, the variables commonly used in financial statement analysis are significantly different before and after adjustments made following audit qualifications. Therefore, users operating with samples obtained from large financial databases must take into account that accounting information disclosed by failed firms usually receives adverse opinions or relevant audit qualifications and, consequently, is unreliable or biased.

Table 2 (continued)

Groupings (n-1)	*Variables*	*B*	*Typical Error*	*Wald*	*Sig.*
Setback	T01	-0.416	1.785	0.054	0.816
	T03	-1.946	1.793	1.178	0.278
	R23	-9.037	2.533	12.730	0.000
	R29C	0.008	0.008	1.173	0.279
	R30	-0.261	0.169	2.396	0.122
	R39	2.226	7.618	0.085	0.770

The interpretation of parameters is not as easy as in a linear regression (the output of the model is the estimated probability of a case to be labeled in a concrete grouping, see Greene, 1998), although the sign of the relationship has the same meaning.

Significant variables for black hole model are: R23 (equity/total assets) and R30 (earnings before interest & tax/interest expenses). Failed growth model includes as significant variables T01 (assets growth) and R23 (equity/total assets); finally the significant variable for setback model is R23.

The default breaking point to consider a case in a concrete category is 50%. Once the estimations are obtained, it is possible to compare the output indicated by the model with the a priori grouping. Table 3 shows the comparison between the forecasted and the observed grouping.

Table 3

Comparison “forecasted – observed”

Observed	*Forecasted*				*% correct*
	B. Hole	F. Growth	Setback	Healthy	
B. Hole	**25**	2*	0	3	**83.3%**
F. Growth	2*	**10***	0	18	33.3%
Setback	3	0	**2**	6	18.2%
Healthy	0	1	1	**111**	**98.2%**
% global	16.3%	7.1%	1.6%	75.0%	80.4%

* In 2 cases, the assigned probability for black hole and failed growth is 100%. If we consider both cases as correctly assigned, the success indexes raise.

A case is classified into a group when the probability obtained in the respective model is higher than 50%. As it can be seen from the table, the global success percentage is greater than 80%. It is especially remarkable that close to 100% of healthy firms were correctly grouped as well as more than 80% of black hole firms. For the other two syndromes, the classificatory success is quite low. In order to study in deep those results, Table 4 presents the number of unsuccessful classifications by the distance to failing date.

Table 4

Unsuccessful classifications, segmented by distance

Distance	*Healthy (H)*	*B. Hole (BH)*	*Failed growth (FG)*	*Setback (SB)*	*Previously unclassified*
Year – 1	0	1 H	4 H	0	5 H
Year – 2	1 SB	0	6 H	3 H	6 H
Year – 3	1 FG	2 H, 1 FG	8 H	3 H	5 H
Total number of errors	2	4	18	6	16
Total number of observations	113	30	30	11	45

H: healthy, FG: failed growth, SB: setback, BH: black hole.

Type II error is only made with one firm (over 40). This healthy firm was erroneously classified as setback in the year -2 (probability, 64%) and as failed growth in the year -3 (probability, 75%). In the year -1 was correctly classified. Regarding type I errors, among black hole firms, there is only one mistake in the year previous to the failing date (this firm is correctly classified in -2 and -3 years with a 100% probability). There are no mistakes for black hole firms in the -2 year, and the year when more unsuccessful classifications occurred is the most distant (year -3, with 3 mistakes).

For failing growth firms, the percentage of correct classifications is not so high, although increases as the failing date approaches. All setback firms were correctly classified in the last year (-1). This success rate diminishes as the distance is higher.

Finally, we performed forecasts also for those firms that were not grouped initially. We considered that the classification was successful when the firm was labeled as failed, with independence of the concrete syndrome. The success rates are as follows: 66% for year -1, 60% for -2 and only 30% in the year -3. For this group those firms that were similar to black hole were once again classified with a higher success rate. In this line, for those 4 firms (12 observations firm-year) there were only 2 mistakes (both in the -3 year). One was considered healthy, and the other was classified as failed, but in other group.

It is necessary to have all the values for all the variables included in the model in order to be able to make the model based classification. In 7 cases (firm-year) we were not able to obtain information for year -4 (needed to build trend ratios). In other 4 cases, R29c presented missing values. For those cases, two alternative models that considered the available variables were calculated. The result of the classification obtained can be summarized as follows: all the healthy (3), black hole (3) and setback (1) firms were correctly identified. The unsuccessful classifications are all concentrated in firms that could not be previously included in any group (3 mistakes, 1 success). In general terms, we obtained a 73% of classificatory success.

Results above suggest that it is possible to identify healthy and black hole firms with a high rate of success. However, the implicit characteristics of the two other syndromes make it difficult to predict the failure more than 1 year in advance; this is not surprising given that the definition of such syndromes implies that those firms are very similar to any other healthy firm until the year prior to failure.

Concluding remarks

The main objective of this paper was to investigate the unique characteristics of failed firms, the factors affecting each particular failure, and the existence of different processes driving to failure.

We performed case studies for each firm in the sample (qualitative analysis) in order to investigate the causes of each failure and the possible identification of syndromes. This analysis allowed us to classify two thirds of the firms in the sample, in three different categories: black hole, failed growth and setback.

"Black hole" firms have a very weak financial situation (negative funds flows from operations, very low/negative equity), which is indicative of a high risk of failure. This firms can be detected and should be avoided.

Unlike "black hole" firms, failure probability of "failed growth" firms is difficult to detect far in advance, since the deterioration of its financial situation becomes evident one or two, at the most, years before failure. In our opinion, the only indication of the risk undertaken by these firms lies in their rapid size increase. Under such circumstances, decision makers should:

- avoid firms with excessively rapid size increases;
- diversify investments in growth firms;
- raise the risk premium for this kind of firms.

Failure probability of "setback" firms was easily sensed several years before failing, due to low interest and debt coverage. However, it is difficult to anticipate the definite failing date because it is usual for these firms to generate positive earnings and to show relatively stable figures that do not seem to point to degradation in the financial situation. In situations like these, decision makers should avoid firms with low interest and debt coverage, at least when these indicators do not reveal a favorable trend.

Finally, statistical tools (quantitative analysis) were used as a validation technique. The result of nominal regressions (multivariate analysis) allowed achieving a high percentage of success in the classification of black hole firms and healthy firms. Only one (over 40) healthy firm was labeled as failed. The percentage of correct classifications of black hole firms exceeded 80%, with the errors concentrated in year -3.

We found those results supporting our hypothesis on failure processes, showing empirical differences between syndromes. The classificatory success is quite different between categories: in black hole firms, the percentage of correct classifications is high. However, for the other syndromes, those percentages are significant in the year prior to failure. Nevertheless, the difference in the classificatory success is not against our failure theory, but quite the opposite, setback and failed growth firms are similar to any normal firm until a concrete event changes their financial equilibrium.

The identification of different syndromes, or paths, leading to failure could be of relevance for research and decision making. Regarding research, it implies a paradigm shift, and opens the possibility to follow new experimental designs. Concerning decision making, it (a) allows to detect and avoid black hole firms and firms in which risk could be assessed and diversified; and (b) raises the opportunity to use decision making systems based on rules. Multinomial models, whose output is an estimation of the probability of failure, are useful in order to implement internal classification models according to Basel II.

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