“Dynamic analysis of different business failure process”

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DYNAMIC ANALYSIS OF DIFFERENT BUSINESS FAILURE PROCESS

Abstract

This work is framed in the research of business failure. We examine a method of analyzing the dynamics of financial failure. The authors examine a method of analyzing the dynamics of financial failure, because our goal is to analyze how the economic and financial indicators show the risk of failure in a group of companies.
Using a sample of 163 companies declared bankrupt or dissolved, the authors show how to depict company trajectories of behavior and movement to terminal failure. They analyze these trajectories to find and describe empirical evidence of the different dynamics of bankruptcy. The authors also show that the estimation of failure risk is more accurate when these different failure trajectories are defined.
In conclusion, the authors can see that there are different failure trajectories. One can use these different trajectories to identify more efficiently the indicators warning of the failure risk of the companies analyzed.

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INTRODUCTION

Researches on business failure should allow us to understand the causes of the failure process, as well as the signals that warn us of this situation before irreversible failure. This information will allow us to design corrective measures to avoid this business failure (Gill de Albornoz & Giner, 2013).

This research is an important issue for anyone associated with the company (shareholders, creditors, policy makers and business managers).

The definition of dependent variable is fundamental, because this aspect defines the concept of business failure and underlies in whole research.

The event used as a definition of failure should be different depending on the model object and intent of the researcher (Balcaen & Ooghe, 2006). Indeed, this is the reason why if is difficult to compare results from different researchers because they do not agree to use the same event to determine failure.

Some researches simplify the concept of business failure by associating a specific moment of time. This time normally coincides with the moment when their activity is interrupted, thus associating the time with the legal definition of failure (Altman, 1968; Ohlson, 1980; Zmijewski, 1984; Taffler, 1984; Mckee, 2000). These studies focused on identifying from a static methodology which variables allow the classification of a company in to the category of sound or failed.

However, the authors understand that failure does not occur suddenly. They know that the failure is a process in time, if not to correct the situation that causes this process it can lead to the interruption of business activity (Argenti, 1976; Altman, 1968; Laitinen, 1991; Ooghe & De Prijcker, 2008; Volkov & Van den Poel, 2012; Lukason, 2012).

To study the failure from this assumption, it is necessary to implement a dynamic methodology that takes into account the deterioration of the company over time. Therefore, making a simplification of reality and using a static methodology is not enough.

Also it must be taken into account that failure does not occur in the same way throughout all the sampled companies (Laitinen, 1991; Arquero et al., 2009; Du Jardin, 2015; Lukason & Laitinen, 2016). This suggests that it is better to use as many models as there are failure processes, rather than one.

For these reasons of business failure, different companies have been studied that follow a similar deterioration trajectory and dynamic analysis methodology. The dynamic methodology that we use is the Cox regression model (1972).

The main objective of our work is to study whether the sample of companies subject to study can detect different paths of deterioration and if there are companies that follow similar paths in this deterioration. We want to study the relationship of each group against the risk of failure. This will allow us to study whether they can obtain significant results in estimating the risk of failure to the total set of companies in the sample regardless of its deterioration path or, on the contrary, is more accurate estimating the risk of failure taking into account that these companies follow different trajectory of decline.

The paper is structured as follows. In the next section, we present of previous work and the main assumptions that make us think. In the second section, we explain the methodology that allows us to determine the different hypotheses that we set. The results of the contrasts are described in the third section and, finally, the main conclusions are presented.

1. REVIEW OF THE LITERATURE AND HYPOTHESES

The studies as precursors of business failure prediction are by Beaver (1966) and Altman (1968). Beaver (1966) analyzed the business failure using an univariate model and Altman (1968) did it using a multivariate one. These works (Beaver, 1966; Altman, 1968) were followed by others as Deakin (1972), Edmister (1972), Ohlson (1980), Taffler (1983), Zmijewaski (1984), Frydman et al. (1985), Mora (1994), Gray et al. (2006), Altman and Sabato (2007), or Pang-Tien et al. (2008). Each of these works made a little contribution but if applied in different contexts, does not show the same reliable result (Jimeno, et al., 2015). Therefore, these works are unable to achieve medium-term forecast (Du Jardin, 2015), because they have not got a conclusive result (Jimeno et al., 2015).

The short-term accuracy of failure prediction models has directed the focus of research towards short-term analyses (Altman et al., 2015).

These studies are based on a static methodology, still trying to analyze the values at different moment of time to study business failure in a period of time (Lukason, 2012; Laitinen & Lukason, 2014). They are based on different specific points in time to study business failure.

In fact, these researches usually assume that failure is the result of a sudden event, as their forecasting time frame does not usually exceed one year. But companies usually show warning signs many years before they fail (Du Jardin, 2011).

Neither of them they take into account the diversity of paths to ultimate failure, some of which can be more chaotic or more gradual than others. These researches also assume that all ratios that are likely to account for failure deteriorate in a systematic manner for all firms that may fail (Laitinen, 1991), and within the same time frame. This means that business failures are embodied in the same early warning signs and the same time (Du Jardin, 2016).

In fact, we have to know that failed companies suffer a gradual process over time, sometimes fail to materialize in the final termination of the activity.

The business failure is considered to be the result of an evolutionary process (González-Bravo & Mecaj, 2011; Korol, 2013). In fact, financial distress of a company is a dynamic ongoing process, and is the result of continuous abnormality of business operation for a period of time (Sun, Li, Huang, & He, 2014).

The business failure starts when the company stands to lose the attainment of its goals. This situation materializes in a period of economic failure. If the economic downturn is not corrected, financial deterioration can begin. This financial deterioration process is what we call phase of financial failure. As a matter of fact, if this phase is continued in time, the company can interrupt their activity.

The firm decline process can vary in length and time (Lukason & Hoffman, 2014). Those authors assume that some failure processes will be more gradual than others.

A few authors considered that there are different levels of business failure. They also considered as well, that there are different processes by which companies can come to total liquidation of the organization (Laitinen, 1991; Abad, et al., 2008; Ooghe & De Prijcker, 2008; Jimeno et al., 2015). In his research, Laitinen (1991) concludes that there are different processes.

Studies such as by Arquero et al. (2009), Jimeno et al. (2015), Lukason and Laitinen (2016) support these failure business processes described and contrasted by Laitinen (1991).

Then, the existence of alternative failure processes in a sample of failed companies makes it necessary to take a prior identification of the different trajectories of these companies.

We have a sample of 163 companies declared bankrupt or dissolved and we want to know if there are different paths of deterioration. For all the above reasons, we considered this question as a first hypothesis.

After verifying this issue, we want to know our main objective that is to study the dynamic trajectory of deterioration of a group failure companies along the pre-interruption of business activity period.

We study the risk of companies' failure in two ways.

On the one hand, we consider that the bankruptcy process is the same for all companies. In this way, we study through a dynamic model by which the set of all sampled companies follow the same process of deterioration. To meet this objective we considered the **hypothesis: the selected financial ratios are related to the risk that the failure in the study period is the same for the set of all sample of companies**.

In this way, we want to know if you can get a significant result in estimating the risk of failure for a group of companies without considering that these companies may follow different path of deterioration. We want to analyze that because Laitinen (1991), Arquero et al. (2009) and Du Jardin (2015) explained us that if you analyze a sample of companies that follow different processes, in a predictive model as a common uniform process could lead to inaccuracies. We want to know that this explanation it's true.

Thus, we want to check what happens if we take into account that there are different trajectories of failure in the sample. There we consider that the companies follow different trajectories of deterioration, the same as in well as Laitinen, Lukason, and Suvas (2014). We study through different dynamics models, one for each group of the different paths of deterioration detected in the sample. To meet this objective, we considered the **hypothesis: the selected financial ratios are related to the risk of the failure in the study period for each group of companies that follow the same failure process.**

We contrast these two hypotheses using a dynamic methodology, in particular, the model of Cox proportional risks. This methodology takes into account the developments in financial ratios during that process as signs of deterioration suffered by the company.

The advantage of the dynamic methodology is that it identifies the time to failure and its relationship with the explanatory factors. But so far studies were conducted that apply this dynamic methodology, have focused on comparing the results contrasting with a dynamic model against those obtained with static methods, such as discriminant analysis or logit (Luoma & Laitinen, 1991; Lee & Urritia, 1996; Shumway, 2001; Chava & Jarrow, 2004; Chancharat et al., 2007; Nam et al., 2008). Or these dynamic models have focused on identifying what factors determine or faster warn about the situation of the company (Männasoo, 2007, Bercovitz & Mitchell, 2007; Saridaskis et al., 2008; Labatut et al., 2009).

Therefore, the main purpose of this paper is to consider the application of survival analysis to study the failure risk of the companies, because we understand that business failure is a process. We considered that Cox proportional hazard model is the best methodology to study business failure deterioration.

2. DATA AND METHODOLOGY

We have developed and tested in this research the model of proportional risks (Cox, 1972).

The Cox regression model allows us to measure and analyze the relationship between the risk of failure and the financial position of the company. This methodology allows us to include time as a variable of the study. Therefore, it is an appropriate methodology to study a problem that has a component that evolves over time and is not always the same: the deterioration of assets.

The model of proportional risks (Cox, 1972) relate the risk algorithm as a linear function of the independent variables (the accounting ratios) on failure time.

The model describes the effect of the covariates on the risk of the occurrence of the outcome.

The risk function has an important assumption that the risk is constant over time.

This methodology allows us to analyze the relationship between the risk of failure and financial ratios over a period of time.

2.1. Sample

The study was carried out in a Spanish context from companies presenting the regular financial statements. The information was obtained from data contained in the SABI (SABI is the Spanish brand of INFORMA D&B. The database INFORMA D&B has been fed from multiple public and private information sources).

The sample consists of firms declared as failed in 2012 and 2013. Their latest available financial information will not be more than twelve months before this date.

The event is the interruption of the activity of the companies analyzed. This event has been associated with legal act of insolvency or dissolution in accordance with the provisions of the Spanish Insolvency Act 22/2003. These companies have been declared insolvent or dissolved.

Listed companies and companies that have to submit consolidated financial statements have been excluded. The reason for this exclusion is that it is difficult to determine whether business group is declared insolvent or dissolved.

In addition, we excluded companies that have been established after 2002 to avoid the inclusion of new companies that have higher risk.

The final sample is composed of 163 companies. The period of study considers the financial information since the end of 2007 until the legal act of insolvency or dissolution. Values are all adapted to the Spanish accounting legislation passed in 2007 to incorporate criteria and standards IAS/IFRS.

2.2. The variables for failure prediction

As evidenced by Garcia et al. (1995), "the choice of the most suitable to use in developing prediction

Table 1. Description of Laitinen (1991) research ratios

Variables	Description*
ROA (%)	BAIT (x 100)/Total Assets
Sales/AT	Net turnover/Total Assets
Annual increase in asset	(Total Assets aco N – Total Assets aco N-1) / Total Assets aco N-1
CF/Sales (%)	Operative Cash Flows*(x100) / Net turnover. *Obtained adding Net Profit + depreciation
PT/AT (indebtedness ratio %)	Total Liabilities (x 100) / Total Assets
AC/PC (liquidity Ratio)	Current Assets/Current Liabilities

Note: * Balance sheet accounts include end balance.

model variables is a fundamental part of it's ultimate success".

A previous literature demonstrates that the financial ratios explain relevant economic and financial information on the situation of the company (Dimitras et al., 1996; Bal, Cheung, & Wu, 2013). We have sufficient evidence about which variables identify failed companies. In fact, profitability, liquidity, leverage and efficiency ratios are the most classical ones showing significant results in business failure prediction studies (Laitinen, Lukason, & Suvas, 2014).

The previous literature on failure prediction has given us sufficient evidence on which accounting ratios reflected the failure symptoms. Therefore, we rely on the previous literature to select the ratios that we consider to rank companies according to their process of deterioration. This allows us to identify different failure processes that follow the companies in the sample.

However, to contrast the other two different hypotheses proposed, we will not use the same ratios used in the classification of companies, but employ the six ratios described by Laitinen (1991). Thus, we contrast the existence of failure processes, on the one hand, and its usefulness in predicting dynamic risk, on the other hand, with two set of different ratios.

We used Laitinen (1991) financial ratios to contrast the other two different hypotheses. Laitinen (1991) showed, with a simplified theoretical model, the five important dimensions which affect the basic concepts of financial statements.

These ratios are normally used in studies of predicting business failure (Laitinen, Lukason, & Suvas, 2014). Table 1 shows the details of these ratios.

The description of these ratios is as follows:

1. Return on Assets (ROA, %): It measures the efficiency of the company in developing its operational functions. This variable has been used previously and with significant results by Altman (1968), Taffler (1984), Frydman et al. (1985), Laitinen and Luoma (1991), Laitinen (1991), Shumway (2001), Chancharat et al. (2007) and Mдnnasoo (2007).

2. Asset turnover (Sales/AT): This ratio shows that the company efficiency when managing these assets (measured per unit). Some of the authors who have used this variable in their research are Altman (1968), Zmijewski (1984), Frydman et al. (1985), Laitinen (1991), Mckee (2000) and Shumway (2001).

3. Annual increase in asset: This ratio informs us of the annual variation of activity in the study period measured per unit. This variable was also used by authors such as Laitinen (1991) and Arquero et al. (2009).

4. CF[1]/Sales (%): This ratio provides information on sales liquidity and is measured as a percentage. This ratio has been studied by Laitinen (1991).

5. Indebtedness ratio (% PT/AT): It favors debt return on equity capital, but provides greater fi-

1 The operating cash flow is estimated from the cash flow statement. But in the cases when we did not have this information from the companies, it has been estimated from EBITDA.

nancial risk. Some of the authors who have used this variable in their research are Beaver (1966), Ohlson (1980), Zmijewski (1984), Frydman et al. (1985), Laitinen and Luoma (1991), Laitinen (1991), Thorley et al. (1996), Shumway (2001), Mдnnasoo (2007), Chancharat et al. (2007) and Christidis et al. (2010).

6. Liquidity ratio (AC/PC): It is the ratio that indicates the company's ability to generate sufficient liquid assets to meet its payment obligations and short-term debt. This ratio is measured per unit. Authors like Beaver (1966), Altman (1968), Ohlson (1980), Zmijewski (1984), Laitinen and Luoma (1991), Laitinen (1991), Lee et al. (1996), Mckee (2000) and Chancharat et al. (2007) used this ratio in their research.

7. We have also included a variable segmentation of the sample:

8. Failure processes: It is a qualitative variable we generate from cluster analysis. It allows us to segment the sample and to respond to the different hypotheses.

These six ratios do not follow a normal distribution. Therefore, we have chosen to use non-parametric or semi-parametric contrasts.

2.3. Hypotheses

First by, we want to know if there are different deterioration paths in our sample. Secondly, we want to know if we can get a significant result in estimating the risk of failure for a group of companies without considering that these companies follow different path of deterioration. And finally, we want to check if we achieve better results when taking into account that there are different trajectories of failure in the sample.

To answer the first objective, we made k-means clustering to know if there are similar groups in the sample. And we made another non-parametric Kruskal-Wallis contrast to confirm if the groups detected correspond to different sub-samples.

To answer the second objective, we made a proportional risk function with the all sampled companies. And finally, to answer the third objective, we made different proportional risk functions as deterioration groups we have detected.

The function proportional risks (Cox, 1972) can be expressed as follows:

$$Ln\left[\frac{h(t,X)}{h_0(t)}\right] = \beta_1 x_1 + \ldots + \beta_i x_i, \qquad (1)$$

where: h_0 is the baseline risk function (the risk function of the outcome occurring for those subjects with $x = 0$); t is time random variable. This variable is continuous and we know when it is going to produce the failure of the company. This variable is measured in years; x_i is, in our case, each of the ratios decribed in Laitinen research (1991).

And β_i are the coefficients measuring the variation of the relative risk when x_j increases by one and all other variables keep constant.

The estimation of the parameters in the Cox regression model is through the contrast of maximum partial likelihood (Cox, 1972, 1975).

We can estimate α coefficient of proportional risk function with the date of the sample. This will allow us to make the following contrasts:

- Statistically significant estimates of β_i coefficients allow us to reject the null hypothesis for each of the ratios studied.

- The likelihood ratio test allows us to determine whether the function of estimated risk is significant for all the companies in the sample. This test is calculated based on the product of likelihoods of all subjects of the sample:

$$2\{log\left(L\left(\beta_0\right)\right) - log(L(\hat{\beta}))\},$$

$L(\beta)$ is the likelihood function; β_0 are the initial values of the coefficients, and $\hat{\beta}$ is the solution when we estimate the model. The Wald Test, as we learn the significance of each of the variables individually. This test contrasts the null hypothesis that the parameter (β) of a particular variable is zero and, therefore, this variable does not dynamically influence in the risk of failure. The significance of the Wald test is related to the p-value in the tables. $\left(\hat{\beta}-\beta_0\right)t\ \sum\Lambda-1\left(\hat{\beta}-\beta_0\right)\ \hat{\beta}$. Where Σ, $\hat{\beta}$ is the covariance matrix estimated; β_0 are the initial values of the coefficients; and $\hat{\beta}$ is the solution when we estimate the model.

This tests the null hypothesis that the parameter (β) of a particular variable is zero and, therefore, this variable does not dynamically influences the risk of failure.

Therefore, these contrast we get to answer the hypotheses of second and third objectives. To test these hypotheses, we will measure the risk of failure from the six ratios described for each of the groups of failed companies that follow the same trajectory of failure.

3. MAIN RESULTS

First of all, we made a classification of the companies. Without extreme cases, we made k-means clustering to identify similar groups in the sample of 132 companies. We made the clustering with usual financial ratios measured at two, three and four years before the event. We obtained three possible clusters. The different cluster distributions are shown in Table 2.

We resolve that best clustering is the one that distinguishes a greater number of ratio differences between clusters. To compare this argument we made a K-W contrast by the ratios described in Laitinen (1991). We show the summary result in Table 3 and the explain contrast in Table 4.

The third cluster detects five groups in which many ratios differences between groups were distinguished. Then, companies in the sample were classified as shown in Table 5.

Table 2. Frequencies by cluster

First cluster		Second cluster		Third cluster	
94	71.21%	90	68.18%	39	29.55%
20	15.15%	17	12.88%	31	23.48%
18	13.64%	15	11.36%	27	20.45%
		10	7.58%	18	13.64%
				17	12.88%
132	100.00%	132	100.00%	132	100.00%

Table 3. Summary contrast K-W by ratios described in Laitinen (1991)

Variable (Laitinen, 1991)	Significant years		
	First cluster	Second cluster	Third cluster
ROA	N2	N2	N2, N3, N4, N5
Rot Assets	N1, N2, N3, N4, N5	N1, N2, N3, N4, N5	N1, N2, N3, N4, N4
Inc Assets	N2*, N3*, N5*	N2, N3, N5*	N5
CF/Sales	N1, N2, N4*	N2	N2, N3
PT/AT	N2, N3, N4, N5	N1, N2, N3, N4, N5	N1, N2, N3, N4, N5
Current ratio	N1, N2, N3, N4, N5	N1, N2, N3, N4, N5	N1, N2, N3, N4, N5

Note: * only 90% significance. ROA = Return on assets; Rot Assets = Net sales/Total assets; Inc Assets = The rate of growth in total assets; CF/Sales = Cash flow/Net sales; PT/AT = Total debt/Total assets; Current Ratio = Current assets/Current liabilities; N1 = one year before failure; N2 = two years before failure; N3 = three years before failure; N4 = four years before failure; N5 = five years before failure.

Table 4. Kruskal-Wallis contrast with the ratios described by Laitinen (1991)

Variables		First cluster		Second cluster		Third cluster	
Variables	**Year**	**Chi-square**	**Sig.**	**Chi-square**	**Sig.**	**Chi-square**	**Sig.**
ROA	N1	3.84	0.15	4.37	0.22	7.06	0.13
	N2	11.08	0.00	21.40	0.00	16.03	0.00
	N3	0.96	0.62	1.47	0.69	18.01	0.00
	N4	0.42	0.81	0.94	0.82	16.97	0.00
	N5	0.91	0.63	0.88	0.83	9.43	0.05
Rot Assets	N1	23.92	0.00	25.00	0.00	24.66	0.00
	N2	27.96	0.00	27.15	0.00	26.35	0.00
	N3	24.68	0.00	24.32	0.00	23.19	0.00
	N4	26.57	0.00	25.90	0.00	24.05	0.00
	N5	25.42	0.00	23.62	0.00	24.64	0.00
Inc Assets	N1	2.87	0.24	2.94	0.40	3.44	0.49
	N2	5.59	0.06	8.42	0.04	7.19	0.13
	N3	5.57	0.06	9.35	0.02	6.00	0.20
	N4	0.89	0.64	1.40	0.71	1.25	0.87
	N5	5.20	0.07	6.23	0.10	11.39	0.02
CF/Sales	N1	6.89	0.03	5.03	0.17	7.27	0.12
	N2	9.28	0.01	7.90	0.05	11.38	0.02
	N3	2.79	0.25	5.57	0.13	9.47	0.05
	N4	5.13	0.08	4.22	0.24	4.84	0.30
	N5	2.62	0.27	3.43	0.33	6.12	0.19
PT/ AT	N1	11.60	0.00	11.26	0.01	18.83	0.00
	N2	39.74	0.00	41.10	0.00	97.34	0.00
	N3	51.27	0.00	50.35	0.00	105.71	0.00
	N4	46.60	0.00	50.51	0.00	90.74	0.00
	N5	32.58	0.00	37.99	0.00	71.88	0.00
Current R.	N1	47.31	0.00	46.28	0.00	53.49	0.00
	N2	66.76	0.00	62.85	0.00	85.26	0.00
	N3	70.90	0.00	75.10	0.00	90.52	0.00
	N4	61.45	0.00	68.01	0.00	82.86	0.00
	N5	50.72	0.00	56.32	0.00	61.54	0.00

Note: N1 = one year before failure; N2 = two years before failure; N3 = three years before failure; N4 = four years before failure; N5 = five years before failure. ROA = Return on assets. Rot Assets = Net sales/Total assets. Inc Assets = The rate of growth in total assets. CF/Vtas = Cash flow/Net sales. PT/AT = Total debt/Total assets. Current Ratio = Current assets/Current liabilities.

The non-parametric Kruskal-Wallis contrast allows us to determine whether the five defined groups correspond to five independent sub-samples. We carry out Kruskal-Wallis (KW) contrast amid pairs of groupings.

It is significant to note that almost all variables show important differences at some point in one group over another during the analysis.

There are differences between sub-samples that are statistically significant, in spite of that the test

Table 5. Contrast of independent sub-samples. Groups taken two by two

Variables	Group I				Group II				Group III				Group IV			
	II	III	IV	V	I	III	IV	V	I	II	IV	V	I	II	III	V
	Signif.				Signif.				Signif.				Signif.			
ROA N1	0.65	0.13	0.42	0.75	0.65	0.20	0.14	0.96	0.13	0.20	0.01	0.18	0.42	0.14	0.01	0.19
ROA N2	0.00	0.00	0.01	0.02	0.00	0.99	0.15	0.11	0.00	0.99	0.18	0.05	0.01	0.15	0.18	0.55
ROA N3	0.30	0.72	0.59	0.01	0.30	0.47	0.02	0.00	0.72	0.47	0.40	0.00	0.59	0.02	0.40	0.02
ROA N4	0.01	0.41	0.27	0.33	0.01	0.06	0.01	0.00	0.41	0.06	0.92	0.07	0.27	0.01	0.92	0.06
ROA N5	0.04	0.29	0.59	0.94	0.04	0.24	0.04	0.00	0.29	0.24	0.61	0.20	0.59	0.04	0.61	0.49
Rot Assets N1	0.97	0.01	0.14	0.71	0.97	0.00	0.07	0.86	0.01	0.00	0.00	0.00	0.14	0.07	0.00	0.28
Rot Assets N2	0.87	0.00	0.30	0.61	0.87	0.00	0.16	0.53	0.00	0.00	0.00	0.00	0.30	0.16	0.00	0.41
Rot Assets N3	0.85	0.00	0.69	0.96	0.85	0.00	0.37	0.83	0.00	0.00	0.00	0.00	0.69	0.37	0.00	0.58
Rot Assets N4	1.00	0.00	0.42	1.00	1.00	0.00	0.36	0.92	0.00	0.00	0.00	0.00	0.42	0.36	0.00	0.32
Rot Assets N5	0.74	0.00	0.72	0.40	0.74	0.00	0.45	0.65	0.00	0.00	0.00	0.00	0.72	0.45	0.00	0.22
Inc Assets N1	0.32	0.43	0.21	0.09	0.32	0.61	0.80	0.54	0.43	0.61	0.98	0.29	0.21	0.80	0.98	0.28
Inc Assets N2	0.12	0.77	0.46	0.04	0.12	0.12	0.34	0.48	0.77	0.12	0.22	0.08	0.46	0.34	0.22	0.10
Inc Assets N3	0.11	0.36	0.11	0.93	0.11	0.08	0.64	0.27	0.36	0.08	0.06	0.46	0.11	0.64	0.06	0.42
Inc Assets N4	0.92	0.79	0.58	0.94	0.92	0.96	0.36	0.86	0.79	0.96	0.31	0.82	0.58	0.36	0.31	0.55
Inc Activo N5	0.31	0.02	0.89	0.04	0.31	0.10	0.26	0.16	0.02	0.10	0.01	0.98	0.89	0.26	0.01	0.02
CF/Sales N1	0.08	0.05	0.41	0.38	0.08	0.14	0.28	0.46	0.05	0.14	0.04	0.07	0.41	0.28	0.04	0.78
CF/Sales N2	0.09	0.01	0.20	0.87	0.09	0.06	0.33	0.10	0.01	0.06	0.02	0.02	0.20	0.33	0.02	0.21
CF/Sales N3	0.93	0.69	0.09	0.01	0.93	0.61	0.10	0.01	0.69	0.61	0.73	0.16	0.09	0.10	0.73	0.17
CF/Sales N4	0.12	0.93	0.03	0.40	0.12	0.42	0.67	0.45	0.93	0.42	0.34	0.88	0.03	0.67	0.34	0.24
CF/Sales N5	0.13	0.84	0.03	0.06	0.13	0.28	0.37	0.44	0.84	0.28	0.15	0.39	0.03	0.37	0.15	0.90
PT/AT N1	0.01	0.02	0.16	0.00	0.01	0.74	0.09	0.02	0.02	0.74	0.25	0.01	0.16	0.09	0.25	0.00
PT/AT N2	0.00	0.00	0.00	0.00	0.00	0.09	0.00	0.00	0.00	0.09	0.00	0.00	0.00	0.00	0.00	0.00
PT/AT N3	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.06	0.00	0.00	0.00	0.00
PT/AT N4	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.95	0.00	0.00	0.00	0.00
PT/AT N5	0.00	0.00	0.03	0.00	0.00	0.02	0.00	0.00	0.00	0.02	0.00	0.48	0.03	0.00	0.00	0.00
Current R N1	0.11	0.00	0.00	0.00	0.11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.71
Current R N2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.15
Current R N3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08
Current R N4	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.17
Current R N5	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.00	0.11

Note: N1 = one year before failure; N2 = two years before failure; N3 = three years before failure; N4 = four years before failure; N5 = five years before failure. ROA = Return on assets. Rot Assets = Net sales /Total assets. Inc Assets = The rate of growth in total assets. CF/Sales = Cash Flow/Net sales. PT/AT = Total debt/Total assets. Current Ratio = Current assets/Current liabilities.

Table 6. Summary contrast independent grouping (K-W)

Variables	Group I				Group II			Group III		Group IV
	Vs Group II	Vs Group III	Vs Group IV	Vs GRoup V	Vs Group III	Vs Group IV	Vs Group V	Vs Group IV	Vs Group V	Vs Group V
PT/AT	Every years	Every years	Every years	Every years	Every years	N2, N3, N4, N5	Every years	N2, N3, N4, N5	N2, N3	Every years
Current R	N3, N4, N5	Every years	Every years	Every years	Every years	N1, N2, N3, N4	Every years	Every years	Every years	N2, N5
Rot Assets	–	Every years	–	N2, N5	Every years	–	–	Every years	Every years	N3
ROA	N2, N4, N5	N2	N2	N2, N3	–	N3, N4, N5	N3, N4, N5	N1	N2, N3	–
CF/Sales	–	N2	N4, N5	N3			N3	N1, N2	N2	N5
Inc Assets	–	N4, N5	–	–	–	–	–	N5	–	–

Note: N1 = one year before failure ; N2 = two years before failure ; N3 = three years before failure ; N4 = four years before failure ; N5 = five years before failure. ROA = Return on assets. Rot Assets = Net sales/Total Assets. Inc Assets = The rate/growth in total assets. CF/Sales = Cash Flow/Net sales. PT/AT = Total debt/Total Assets. Current Ratio = Current Assets/Current liabilities.

Table 7. Groups of companies that follow different failure processes

Failure processes	Number of companies	Percentage (%)
Process I	18	13.63%
Process II	31	23.42%
Process III	17	12.87%
Process IV	39	29.54%
Process V	27	20.45%
Total	132	100%

Table 8. Proportional risk function for all companies of the sample (like these following the same failure process)

Omnibus test				
Overall score				
Step (iterations)	–2 log likehood	Chi-square	gl	Sig.
1€	1144.21	8.28	11.00	0.69
2b	1144.27	8.19	10.00	0.61
…..	…..	…..	…..	…..
9i	1147.07	4.21	3.00	0.24
10j	1148.26	3.05	2.00	0.22
11k	1148.98	2.58	1.00	0.11
12l	1150.62	…..	…..	…..

Table 9. Proportional risks function for each processes failure detected in the sample

	Process I (18 cases)				**Process II (28 cases)**			
	B	**p-value**	**Wald**	**Exp(β)**	**β**	**p-value**	**Wald**	**Exp(β)**
ROA	–0.018	0	18.28	0.983	0.003	0.498	0.46	1.003
Indebtedness ratio	–0.028	0.002	9.23	0.972				
CF/Sales					0	0.019	5.523	1
Inc Assets	2.072	0.035	4.434	7.942				
–2 Log likehood	143.187				251.73			
Chi-square	23.09	0			10.55	0.005		
	Process III (16 cases)				**Process IV (38 cases)**			
	B	p-value	Wald	Exp(β)	β	p-value	Wald	Exp(β)
ROA					–0.012	0.002	9.494	0.988
Rot Assets	–2.124	0.006	7.436	0.12				
Indebtedness ratio					–0.016	0.004	8.34	0.984
Current ratio	0.047	0.048	3.9	1.048	–1.426	0.001	11.312	0.24
Inc Assets								
–2 Log likehood	125.451				323.71			
Chi-square	28.121	0			14.186	0.003		
	Process V (27 cases)							
	B	p-value	Wald	Exp(β)				
ROA	0.02	0	10.25	1.02				
Indebtedness ratio	0.03	0	10.97	1.03				
Current ratio	–0.32	0.3	1.06	0.72				
Inc Assets	–1.28	0.22	1.5	0.28				
–2 Log likehood	241.14							
Chi-square	10.26	0.02						

does not use the same variable that have been used by the clustering. We show the details of this contrast in Table 6 and the summary results in Table 6.

Therefore, there are five groups and this allows us to distinguish the process prior degradation and predict failure of the organization.

Table 8 describes the distribution of cases to the group that relate to the processes of failure: there are five different groups (processes I to V).

Once classified the companies, we proceed to discuss the results of the hypotheses 2 and 3.

Testing the hypothesis of the second objective, we can see in Table 8 that we cannot estimate the risk of failure function for all the companies as that these follow the same trajectory to failure.

Testing the hypothesis of third objective, we can see in Table 10 that the risk of failure for each sample clusters can be estimated. We can test that the p-value is significant for each models generated with Laitinen (1991) variables. Therefore, we can say that the risk of failure is anticipated when we study these risk in the different failure processes.

We can see in Table 10 that the risk suffering each clusters is defined by a set of specific variables. The process I is defined by the ROA and indebtedness ratio. The process II is identified by the ROA and the cash flow to net sales ratio. The process III is identified by the asset turnover and current ratio. The process IV is identified by the ROA, indebtedness and current ratio. The process V is identified by the ROA, indebtedness, current ratio and annual increase in asset. These set of variables, which identify the risk in a cluster, are different from other set of variables who define the risk in another sample cluster. Still, there are variables that identify the risk of failure in several different processes.They are the ROA, current ratio and indebtedness ratio.

CONCLUSION

The previous literature focused on determining which variables distinguish sound companies from failed (Lukason, 2012). For this research, they used a static methodology with a static variable, but we understand that companies failure is a process. Therefore, we think that we need a dynamic methodology for the study of failure prediction.

In this research, we consider the variable to study as a risk of failure. We only study failed entities because we studied if there are different trajectories of deterioration of a group of failed companies along the pre-interruption of business activity period. We study the risk of companies' failure in two ways. On the one hand, we study the risk all of companies of the sample as all of them follow the same trajectory of deterioration. On the other hand, we study the risk of companies failure once having classified these companies in deterioration process.

One important conclusion is that there are different processes of business failure in our sample. We tested the risk to determinate that group companies that carry different trajectories to failure are not the same.

Therefore, we know that if we want to study failure prediction we have to take into account two important factors. Firstly, business failure is an evolutionary process. It makes us consider that trajectory of deterioration of the company is not the same at all over the process. Secondly, we consider that the bankruptcy process is not the same for all companies, and, as a consequence, that the warning signs of failure do not occur in the same way and at the same time.

Now we contrast that the warning signs of failure do not occur in the same way, because we check that the risk suffering each cluster is defined by a set of specific variables. These set of variables, which identify the risk in a cluster, are different from other set of variables which define the risk in another sample cluster. But there are variables that identify the risk of failure in several different processes. In this way, we propose to study whether these different variables identify the risk at the same time in different processes.

And another limitation that should be noted is that our study only focused on analyzing companies that have come to liquidation, excluding study of companies still active. This has been true for easy identification in the sample of companies of different groups of companies that follow similar processes of deterioration. However, we believe that once you can get to establish patterns of behavior in the process of failure, we would propose as a future line of work studying the failed companies classified by processes together with a sample of sound companies.

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