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Trend of Financial Ratios in the Business Failure Process

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Abstract— *The main objective of this paper is to investigate how financial indicators and the trends of these financial indicators describe business failure process. We use a method of analyzing the dynamics of financial failure in a sample of companies.*

We use a sample of 163 companies which were declared bankrupt or dissolved, we depict the companies' behavior trajectories on their path to final failure. We analyze these trajectories to discover and describe empirical evidence of the different dynamics of bankruptcy.

In conclusion, we will see that there are different failure trajectories. We can use these different trajectories to identify the indicators that warn of the risks of failure of the companies in the sample. Finally, we prove that we will obtain more information in the model when included financial indicators with their trend.

Keywords— *Bankruptcy, Business failure, Failure process, Financial ratio, Dissolution, Insolvency, Trend of financial ratios.*

I. Introduction

The researches on business failure should enable us to understand the causes of degradation process of an organization, as well as the signals that can be identified before the irreversible actual failure. This knowledge will allow us to design corrective measures to avoid this business failure [1].

This research is a critical issue for anyone associated with the company such as shareholders, creditors, policy makers and business managers.

In the study of business failure the definition of the dependent variable is fundamental. This aspect is also defining the concept of failure that underlies all research.

The event used as a definition of failure should be different depending on the model object and intent of the researcher [2]. Indeed, that is the reason which is difficult to compare results from different research because they do not agree to use the same event to determine failure.

The bankruptcy prediction research has focused on identifying which variables allow classifying to healthy companies unsuccessful. These researches are based on statistics distances between groups of companies, healthy and failed, from different economic and financial indicators [2]; [3]; [4]; [5]; [6]. These researches have made a lot of contributions to the bankruptcy prediction study. They have provided new approaches and more robust statistical tools [7], although these studies have several limitations. First, the methodology used is static, these not measure the distance of the undertakings time to failure [4]. In previous studies, some authors apply a methodology of dynamic contrast. Indeed, in these researches they compare the superiority of dynamic models on static model. The problem with these dynamic studies is that they focus on comparing this dynamic methodology with other static methodologies [8], [9], [10], [11], [12], [13]. Other dynamic studies have focused on identifying what factors determine and alert more quickly the situation of the company [14], [15], [16], [7]. The final limitation to note is that the prediction of bankruptcy is studied assuming that the failure occurs in the same way across all the companies in the sample. The studies assimilate the signals that warn of the companies situation are the same for all companies [17], [18] and [19].

These studies tend to associate failure at the time of interruption of business activity [20], [21], [22], [23], [24]. However, it is understood that the failure does not occur suddenly, but is a process in time if not corrected the situation that can cause the stopping of the activity of the company [25], [20], [17], [26], [27], [5].

Therefore, this leads us to want to study a companies that declared bankrupt or dissolution, throughout the period before the interruption of its business with the dynamics methodology and taking into account the deterioration time path way.

The business failure is considered to be the result of an evolutionary process [3]; [28]. 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 [6].

We understand that business failure begins when the company misses the achievement of his goals, and materializes in a period of economic failure. Failure to correct this economic downturn, it can lead to a financial deterioration. This process of financial deterioration is what we call stage of financial failure. In fact, if this stage is prolonged in time, the trajectory of decline of business can lead to the interruption of company's activity.

The firm decline process can vary in length and time [29]. Those authors assume that some failure processes will be more gradual than others. Therefore, we believe that companies can follow different processes of failure depending on the intensity with which undergoes stages of their gradual deterioration.

Then, the existence of alternative failure processes in a sample of failed companies, make it necessary to take a prior identification of the different trajectories of these companies. Companies follow different strategies of decline. If we analyze a sample of companies that follow different processes in a predictive model as a common uniform process can lead to inaccuracies. This is may be the reason that the optimal failure prediction model for each process it be different based on different financial ratios [17]; [18] and [19].

In this research, we do not consider the variable to study as a dichotomous variable that distinguishes healthy entities failed as another research, because our goal is not to investigate those variables differ from one another better. Our main objective is to study the dynamic trajectory deterioration of a group failure companies along the pre-interruption of business activity period. We study the risk of companies failure once have been classified these companies in deterioration process. We also intend to identify which ratios described in the previous literature of failure allow us to better classify the companies between different processes of failure and if the trend of these ratios provide more information on the risk of these companies.

This paper focuses on detecting what economic and financial factors together with the tendency of these factors who show warning signs when companies go through a deteriorating situation using a methodology dynamic contrast hypothesis (in particular the model of Cox proportional hazards). This methodology takes into account the developments in financial ratios during that process as signs of deterioration suffered by the company. We want to study what indicators reveal the risk of deterioration of the company several years before the final cessation of business activity and if the trend of these factors provides more information about these risk.

Therefore, we set several objectives in this paper, which will be summarized in: i) to detect different processes leading to failure, because we want study the risk of failure in each process; ii) to study the risk of failure of each detected processes in a sample of failed companies with a dynamic model. We want to know what economic and financial factors show signs of risk before discontinuance of its activity. And we also want to know if tendencies of variables provide more dynamism and information to the study.

The presentation is structured as follows. In the next section we expose an introduction review of previous work. In the second section we explain the different objective we propose in our study. In the third section we explain the methodology. The results of the contrasts are described in the fourth section and, finally, the main conclusions are presented.

II. Review of the Literature and Hypotesis

[30] and [20] are the precursors of study *business failure prediction*. These authors analyzed the business failure using univariate and multivariate models. Characteristic papers of this period are, among others, those of [31], [32], [33], [23], [22], [34], [35], [36], [37], or of [38]. This period papers have a certain predictive instability and unreliability if applied in different contexts initially used to, so you can get to question their predictive ability. Then these works have not led to conclusive result, because they are unable to achieve medium-term forecasts [19].

These studies are based on a static methodology, still trying to analyze the values at different moments of time to study business failure on a period of time [5] and [39]. They are based on different specific points in time to study business failure, when in fact failed companies suffer a gradual process over time, sometimes fails to materialize in the final termination of the activity.

Therefore, the main problem with these previous works is that they are not dynamic in nature. But, there are other models that include the tendency of variables to improve the selected financial ratios. This is a good step to introduce dynamism to these models [40].

At the same time as the [30] and [20] approach, another line of research was developed. This research was focused on analyzing the failure as a dynamic process. There are only a few authors have specifically studied that the failure processes of collapsed firms [25], [17], [26], [18], [19].

Several authors, including [41], [17], [42], [26], considered, first, that there are different levels of failure in relation to the economic and financial characteristics of the firms and, second, that there are different processes by which organizations can cross to reach the total liquidation of the organization. In their research, [17] concludes that there are different processes or failure syndromes, which are summarized below:

1. *A chronic failure firm:* this group is made up of organizations that show detectable signs of failure up to four years before. These signs are sampled in variables such as profitability ratios, the ratio of cash flow to sales, the ratio of total debt to assets and liquidity ratios.
2. *A revenue financing failure firm:* this group consists of companies in which the impairment occurs two years before the final collapse. The variables used to detect it include low cost, low cash flow ratio to sales, poor revenue financing, and low asset turnover.
3. *An acute failure firm:* this group includes companies where material differences among ratios are not detectable up to the previous year to fail when a general deterioration of all ratios is perceived. Only the lack of solvency is observed in advance.

These failure processes described and contrasted empirically by [17] are empirically supported by other studies such as [18] who relate the causes of failure with its evolution and the ratios of the failed organization based on a sample of companies in cease of payments three years prior to the suspension.

We have to take into account two important factors. Firstly, understand that 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, does not occur in the same way and at the same time.

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. Then, the present analysis is restricted to the Cox proportional hazard model and is a dynamic methodology. This methodology allows us to analyze the relationship between the risk of failure and financial ratios over a period of time.

We know that different traditional researches of business failure have focused on identifying which variables distinguish healthy companies of failed. These researches show that the economic and financial structure of the companies that fail seems to be different from the ones that do not [3].

The financial variables that distinguish between the failed and not failed companies are not the same as those that distinguish between failed companies and firms with difficulties [3].

In this sense, we understand that warning indicators of a failure process are different according to the point in the process where the company is located. In fact, we believe that the warning signs emitted by companies that are in a process of deterioration are different from other companies still another process.

Therefore, a previous literature demonstrates that the financial ratios explain relevant economic and financial information on the situation of the company [43], [40]. We have sufficient evidence about which variables identify troubled companies. In fact, profitability, liquidity, leverage and efficiency ratios are the most classical ones significant result in business failure prediction studies [39].

We have selected financial ratios for the development of our study. But, the ratios offer values at different moments of the time. Then these ratios as static figures do not a process and we are trying to study a dynamic process with static information and dynamic methodology. We could also apply changes in financial statement figures to consider the tendencies of these ratios, because this is a form to introduce dynamism to these models [40]. Accordingly, we study ratios and their tendencies, because ratios reflect a firm's financial position statically at different points of time and the changes show the dynamics in terms of the speed of their improvement or decline. Both of these measures must be included in analysis to have a complete understanding of the development of failure as a process [39].

[17] in his paper made a mathematical relationship between different ratios that collect relevant information from all the economic and financial dimensions of the company. This author, Erkki K. Laitinen, is one of the most published evidence on the existence of different processes of failure [17], [44], [45], [39]. And therefore, we use in our study the six ratios and their tendencies selected by [17]

We, as [25], consider that there are different processes of failure. In fact, researches of [17] and [18] show empirical evidence on the existence of such failure processes.

We believe that a failure processes are more gradual than others. In fact, we believe that in a random sample of companies declared bankrupt or dissolution, can distinguish different trajectories of decline [19]. Each trajectory of decline symbolizes the change in the financial health of a companies' subset that share the same behavior. We therefore propose to group the companies according to the trajectory followed in the process of deterioration to study the relationship between each process and the risk of failure.

According to the above, we consider the following three objectives of study.

The first objective is to study the risk of bankruptcy of companies according to the trajectory of decline following these companies.

To do this, we classify the sample companies from the similarities and differences that show the economic and financial ratios during the five years prior to the final decline.

Subsequently, we measure the proportional hazards function for each grouping of businesses detected.

To meet this goal we propose the following hypothesis:

First hypothesis: The selected financial ratios do not identify the risk of failure for each group of companies that follow the same failure process.

We expect to find significant relationships between the ratios and the risk of failure in each of the different processes of failure.

As the ratios offer values at specific moments of time. Despite using a dynamic methodology that allows us to study the information provided in these ratios over time, we are using as static information. But, we know that the tendency of ratios give us a dynamic information [40]. So we want to check if only are used the tendency of these ratios gives us dynamic information about the risk of failure.

The second objective is to study the relationship between each process and the risk of failure from trends ratios.

To get this objective, we propose the following hypothesis:

Second hypothesis: The trends of selected financial ratios do not identify the risk of failure for each group of companies that follow the same failure process.

But [39] said that both of these measures, ratios and trends of ratios, must be included in analysis to have a complete understanding of the development of failure as a process.

Therefore, we want to see if the study the risk of failure with the variables and the tendency of variables we get more information about the process.

Then, the third objective is to study the relationship between each process and the risk of failure from the ratios and trends of these ratios.

Therefore, we propose the following hypothesis:

Third hypothesis: The selected financial ratios and trends of these ratios do not identify the risk of failure for each group of companies that follow the same failure process.

These hypotheses allow us if the trends of the variables provide valuable information about the risk of failure in the different processes of deterioration.

III. Data and Methodology

We have used the proportional hazards assumption [46].

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 analyze a problem having a component that evolves over time and is not always the same: the deterioration of assets.

The proportional hazards model [46] uses a linear function to relate the risk algorithm and the independent variables (the accounting ratios) over a period of time.

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

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

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

A. Sample

The study was carried out in a Spanish context from companies presenting the regular financial statements format. 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 been 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 are 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.

B. The variables for Failure Prediction

As evidenced by [47] "the choice of the most suitable to use in developing prediction model variables is a fundamental part of the ultimate success of it."

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 need, to rank companies according to their process of deterioration. This allows us to identify different failure processes that follow the companies in the sample. Annex Table 7 shows a breakdown of these ratios and previous studies that have shown their information relevance.

However, to check the different hypotheses proposed, we will not use the same ratios used in the classification of companies. But, we will use the six ratios described by [17]. Thus, we verify the existence of failure processes on one hand, and its usefulness in predicting dynamic hazard for another, with two sets of different ratios.

We have divided the indicators of default into four branches: profitability, liquidity, leverage and efficiency.

We used financial ratios that describe the most relevant dimensions in prediction of business failure, as [17] show: (1) profitability, (2) growth, (3) the capital intensiveness, (4) loan-taking intensiveness, (5) the harmony of debt financing, and (6) the interaction of profitability, growth, and the capital intensiveness in terms of the sufficiency of revenue financing.

These ratios reflect the basic financial dimensions and are normally used in studies of predicting business failure [39]. Table 1 shows the details of these ratios.

TABLE I. Description of Laitinen research ratios

Variables	Description[1]
ROA (%)	BAIT (x 100) / Total Assets
Sales/AT	Net turnover/Total Assets
Annual increase in asset	(Total Assets $_{\text{año N}}$ - Total Assets $_{\text{año N-1}}$) / Total Assets $_{\text{año N-1}}$
CF / Sales (%)	Operative Cash Flows*(x100) / Net turnover
PT/AT (Indebtedness ratio %)	Total liabilities (x 100) / Total Assets
AC/PC (Liquidity Ratio)	Current Assets/Current liabilities

[1] Balance sheet accounts include End Balance
*Obtained adding Net Profit + depreciation

The description of these ratios and expected relationship with risk is:

1. *Return on Assets (ROA %)*: It measures the efficiency of the company in developing its operational functions. It can be said that the higher this ratio, better is the ability of the entity to generate profits and, therefore, lower is the risk of failure. We hope to get an inverse relationship between this ratio and the failure risk of the company. This variable has been used previously and with significant results by [20], [23], [34], [8], [17], [10], [12] and [14].
2. *Asset turnover (Sales/AT)*: These ratio show that the company efficiency when managing these assets (measured in per unit). We hope to get an inverse relationship between this ratio and the failure risk of the company. Some of the authors who have used this variable in their research are: [20], [22], [34], [17] [24] and [10].
3. *Annual increase in asset*: This ratio informs us of the annual variation of active in the study period, measured in per unit. They have also used this variable author like [17] and [18].
4. *CF [1]/ Sales (%)*: This ratio provides information on sales liquidity and is measured as a percentage. This ratio has been studied by [17]. We hope to get an inverse relationship between this ratio and the failure risk of the company.
5. *Indebtedness ratio (% PT/AT)*: This ratio shows us the level of the company indebtedness as a percentage. It favors debt return on equity capital, but provides greater financial risk. We can expect a positive relationship between debt and the risk of business failure. Some of the authors who have used this variable in their research are: [30], [33], [22], [34], [8], [17], [10], [14], [12].
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 in per unit. Therefore, we can expect to get an inverse relationship between this ratio and the failure risk of the company. Authors like [30], [20], [33],

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

[22], [8], [17], [24] and [12] has been used this ratio in their research.

We have also included a variable segmentation of the sample:

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

Annex Table 8 collects evidence of normality of these six ratios. It can be seen that does not follow a normal distribution. Therefore, we have chosen to use non-parametric or semi-parametric contrasts.

C. Hipothesis

First we will study the risk of bankruptcy of companies according to the trajectory of decline following these companies with the financial ratios that report profitability, liquidity, indebtedness and efficiency, in the five years prior to the suspension of business activity (objective 1). Secondly, we want study the relationship between each process and the risk of failure from trends of variables profitability, liquidity, indebtedness and efficiency for the five year before the failure (objective 2). And finally, we want to research the relationship between each process and the risk of failure from the ratios and trends of these ratios (objective 3), because we want to know which of these variables provides more information and thus determine what function proportional hazards represents the best prediction of risk of failure.

To answer the first objective we made a proportional hazard function only with the six variables of [17] study. To answer the second objective we made a proportional hazard function only with the trend of [17] study variables. And finally, to answer the third objective we made a proportional hazard function with both types of variables (ratios and their trends).

The function proportional hazards [46] can be expressed as following:

(1) $\text{Ln}\,[h(t, X) / h_o(t)] = \beta_1 x_1 + \ldots + \beta_i x_i$

Where:

h_0 is the underlying hazard function, that is the initial risk at the time of the study period.

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 described in Laitinen research (1991).

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

The estimation of the parameters in the Cox regression model is through the contrast of maximum partial likelihood [46].

We can estimate α coefficient of proportional hazard 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 the whole of all the companies in the sample. This test is calculated based on the product of likelihoods of all subjects of the sample:

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

$L(\beta)$ 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 contrast the null hypothesis that the parameter (β) of a particular variable is zero and, therefore, this variable does not dynamically influences in the risk of failure. The significance of the Wald test is related to the p-value in the tables. $(\hat{\beta}-\beta_0)^t \sum\Lambda^{-1}(\hat{\beta}-\beta_0)\ \hat{\beta}$. Where $\sum'_{\hat{\beta}}$ 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 test 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.

We also calculate the Akaike Information Criterion (AIC) for comparing the goodness of fit of two functions, we have to know that the log-likelihood and the number of covariable. The function that better estimates the dependent variable is the one with less value of AIC [48].

Therefore, these test we get to answer all the hypotheses that we set. These hypotheses are:

First hypothesis: The selected financial ratios identify the risk of failure for each group of companies that follow the same failure process.

To test these hypotheses we will measure the risk of failure from the six ratios described for each of the groups failed companies that follow the same trajectory to failure.

We know as the ratios offer values at specific moments of time. Despite using a dynamic methodology that allows us to study the information provided in these ratios over time, we are using static information. But, we know that the tendency of ratios give us a dynamic information [40]. Therefore, we want to know what happen if we only use dynamic information like the tendency of these ratios. Then, we study the relationship between each process and the risk of failure from trends ratios.

Second hypothesis: The trends of selected financial ratios identify the risk of failure for each group of companies that follow the same failure process.

[39] said that both of these measures, ratios and trends of ratios, must be included in analysis to have a complete understanding of the development of failure as a process.

Therefore, we want to see if we study the risk of failure with the variables and the tendency of variables, we get more information about the process.

Third hypothesis: The selected financial ratios and trends of these ratios identify the risk of failure for each group of companies that follow the same failure process.

The cases used in contrasting hypotheses are a total of 132 companies. There are 81.5% of cases initially considered[2].

IV. Main Results

First at 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 obtain three possible clusters. The different cluster distributions are shown in Table II.

TABLE II. 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%**

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 [17] We show the summary result in Table III and the explain contrast in table IV.

TABLE III. 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

* 90% significance.
ROA= Return on assets
Rot Assets = Net sales / Total assets
Inc Assets = 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.

[2] We have chosen to detect and exclude cases of extreme observations. The variables of this study are financial ratios and these are very sensitive to having extreme values. To remove outliers and lose the minimum valid for the study information as possible, we have chosen to make a hierarchical cluster from the values of the ratios of the previous literature (described in Table 7 of Annex) for two, three and four years before the final demise of the company. Annex Table 9 shows the grouping made by hierarchical cluster: the cluster 4 and collected following companies have higher extreme values considering the ten measured ratios. They represent 18.5% of the initially selected cases.

TABLE IV. Kruskal-Wallis contrast with the ratios described by Laitinen (1991)

		First Cluster		Second Cluster		Third Cluster	
	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

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

The non-parametric Kruskal Wallis contrast allows us to confirm whether the five identified groups correspond to five independent sub-samples. We perform a Kruskal Wallis (KW) contrast between pairs of groupings.

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

We find that differences between sub-samples are statistically significant, despite the fact that the test does not use the same ratios that have been used by the clustering. We show the details of this contrast in Table V and the summary result in Table VI.

International Research Journal of Advanced Engineering and Science
ISSN (Online): 2455-9024

Therefore, we can say that the five groups show different values for almost all selected financial ratios. These allow us to distinguish the process prior degradation and predict failure of the organization.

TABLE V. Contrast independent sub-samples. Group 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

N1= oneyear 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 = 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 VI. Summary contrast independent grouping. Groups taken in pairs.

	Group I				Group II			Group III		Group IV
Variables	**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		

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 investment ratio
Rot Assets = Net sales/ Total Assets
Inc Assets = 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 VII describes the distribution of cases to the group that relate to the processes of failure: there are five different groups (Groups I to V).

TABLE VII: Groups of companies that follow different 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 %

Once classified companies, we proceed to discuss the results of each hypothesis.

In table VIII, we show summarize of the significant models we have been obtained.

Taking into account that we are testing the hypothesis of the first objective, we can see in table VIII that we can estimate the risk of failure function for each sample clusters. We can see that the p-value is significant for each models generated with [17] variables. Therefore, we can say that we anticipate the risk of failure for the processes of failure detected in the sample from [17] variables.

We can see (table VIII) that the risk suffering each clusters is defined by a set of specific variables. The process I is identified 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 and are the ROA, liquidity ratio and debt.

TABLE VIII: Model with Laitinen (1991) variables

	Process I (18 events)				***Process II*** (28 events)			
	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
Rot Assets								
PT/AT	-0,028	0,002	9,23	0,972				
CF / Sales					0	0,019	5,523	1
Current R								
Inc Assets	2,072	0,035	4,434	7,942				
-2 log likehood	143,187				251,73			
Chi- squared	23,09	0			10,55	0,005		
AIC	155,187				259,73			
	Process III (16 events)				***Process IV*** (38 events)			
	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				
PT/AT					-0,016	0,004	8,34	0,984
CF / Sales								
Current R	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- squared	28,121	0			14,186	0,003		
AIC	133,451				335,71			
	Process V (27 events)							
	B	**p-value**	**Wald**	**Exp(β)**				
ROA	0,02	0	10,25	1,02				
Rot Assets								
PT/AT	0,03	0	10,97	1,03				
CF/ Sales								
Current R	-0,32	0,3	1,06	0,72				
Inc Assets	-1,28	0,22	1,5	0,28				
-2 log likehood	241,14							
Chi- squared	10,26	0,02						
AIC	253,14							

ROA= Return on investment ratio
Rot Assets = Net sales/ Total Assets
Inc Assets = Rate of growth in total assets
CF/Sales = Cash Flow/ Net sales
PT/AT = Total debt/ Total Assets
Current Ratio = Current Assets/ Current liabilities

Secondly, with regard to hypothesis testing of the second objective, we can see in table IX that in three of the five processes were obtained no significant results when estimating the risk function. Then, the processes I, II and III don´t have significant results were seen in the p-value that exceeds 0,05.

The processes IV and V have significant results. We can see (table IX) that the risk suffering each clusters is defined by a set of specific trends of variables. The process IV is identified by the trend of current ratio, the trend of indebtedness ratio. The process V is identified by the trend of

International Research Journal of Advanced Engineering and Science
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cash flow to net sales ratio, the trend of indebtedness ratio and trend of assets turnover ratio.

Then, we compare the AIC contrast of theses model (trends of variables) with the AIC test of [17] variables models. And, we can see (in table VIII and IX) that the risk of failure is better defined with the variable model than the trend of variable model.

TABLE IX: Model with trend of Laitinen (1991) variables

	Process I (18 events)				***Process II*** (28 events)			
-2 log likehood *Chi*- squared *AIC*	160,54	0,24			244,329	0,185		
	Process III (16 events)				***Process IV*** (38 events)			
	B	**p- value**	**Wald**	**Exp(β)**	**β**	**p- value**	**Wald**	**Exp(β)**
Inc. ROA								
Inc. Rot Assets								
Inc. PT/AT					0,083	0,020	5,430	1,087
Inc. CF/ Sales								
Inc. Current R					-0,264	0,486	0,485	0,768
Inc Assets								
-2 log likehood *Chi*- squared *AIC*	141,914	0,271			342,753 11,303 350,75	0,004		
	Process V (27 events)							
	B	**p-value**	**Wald**	**Exp(β)**				
Inc. ROA								
Inc. Rot Assets	0,21	0,54	0,38	1,24				
Inc. PT/AT	-1,1	0,11	2,54	0,33				
Inc. CF/ Sales	0,00	0,04	4,3	1,00				
Inc. Current R								
Inc Assets								
-2 log likehood *Chi*- squared *AIC*	241,14 10,26 253,14	0,02						

Inc. ROA= Rate of growth of Return on investment ratio
Inc. Rot Assets = Rate of growth of Net sales/ Total Assets
Inc Assets = Rate of growth in total assets
Inc. CF/Sales = Rate of growth of Cash Flow/ Net sales
Inc. PT/AT = Rate of growth of Total debt/ Total Assets
Inc. Current Ratio = Rate of growth of Current Assets/ Current liabilities

Finally, respect to hypothesis testing of the third objective, we can see in table X that we can estimate the risk of failure function for each sample clusters. We can see that the p-value is significant for each models generated with [17] variables and their trends. Therefore, we can say that we anticipate the risk of failure for the processes of failure detected in the sample from [17] variables and their trends.

We can see (table X) that the risk suffering each clusters is defined by a set of specific variables. The process I is identified by the asset turnover, the indebtedness ratio and their trends. The process II is identified by the cash flow to net sales ratio, the indebtedness ratio, trend of current ratio and the trend of indebtedness ratio. The process III is identified by the asset turnover, current ratio, indebtedness ratio, the trend of asset turnover and the trend of indebtedness ratio. The process IV is identified by the indebtedness and current ratio and their trends. The process V is identified by the indebtedness, current ratio, the trends of these variables and the trend of cash flow to net sales ratio. 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 all different processes are the indebtedness ratio and their trend.

Now, we compare the AIC contrast of the three type of model that we made (type one: variable model, type two: trends of variables model and, type three: variable and trend of variable model). And, we can see (in table VIII, IX and X) that the risk of failure is better defined with the variable and trend of variable model than the other two types models.

Therefore, we can say that the trends of the variables alone do not define the risk of business failure. But they provide information about the risk of failure when included in the model along with the variables.

V. Conclusion

[30] and [20] are early research about companies' failure. There is large variety of literature about that. They have made many research of bankruptcy prediction with different methods of analysis, different samples, countries and different periods [31], [32], [23], [21]; [22]; [34]; Serrano and Martin, 1988; [35]; [36];. [37]; or [38].

However, the predictive accuracy of these studies decreases as the ratios measured for the contrasts time away from the final decision of the company. These researches are most effective when measurements are used ratios in final company period.

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ISSN (Online): 2455-9024

TABLE X: Model with Laitinen (1991) variables and trend of these variables

	Process I (18 events)				***Process II*** (28 events)			
	B	**p-value**	**Wald**	**Exp(β)**	**β**	**p- value**	**Wald**	**Exp(β)**
CF/ Sales					0,000	0,018	5,6	1,000
Rot Assets	0,504	0,017	5,669	1,65				
Current R								
PT/AT	-0,049	0,000	25,29	0,95	0,024	0,025	5,021	1,025
Inc. CF/ Sales								
Inc. Rot Assets	-1,418	0,004	8,40	0,24				
Inc. Current R					0,374	0,168	1,901	1,45
Inc. PT/AT	2,870	0,000	23,03	17,63	-1,831	0,049	3,881	0,16
-2 log likehood	133,076	0,000			234,627	0,001		
Chi- squared	31,43				17,65			
AIC	149,076				250,62			
	Process III (16 events)				***Process IV*** (38 events)			
	B	**p- value**	**Wald**	**Exp(β)**	**β**	**p- value**	**Wald**	**Exp(β)**
CF/ Sales								
Rot Assets	-2,518	0,005	7,753	0,081				
Current R	0,056	0,088	2,915	1,057	-2,645	0,000	21,95	0,071
PT/AT	0,037	0,071	3,256	1,038	-0,027	0,001	10,757	0,973
Inc. CF/ Sales								
Inc. Rot Assets	1,066	0,000	14,714	2,9				
Inc. Current R					1,928	0,002	9,775	6,976
Inc. PT/AT	-6,149	0,042	4,142	0,002	1,589	0,001	11,889	4,899
-2 log likehood	109,67	0,000			312,163	0,005		
Chi- squared	38,89				14,67			
AIC	129,670				328,163			
	Process V (27 events)							
	B	**p-value**	**Wald**	**Exp(β)**				
CF/ Sales								
Rot Assets								
Current R	-2,71	0,01	6,56	0,07				
PT/AT	0,11	0,000	20,66	1,11				
Inc. CF/ Sales	0,00	0,12	2,42	1,00				
Inc. Rot Assets								
Inc. Current R	3,01	0,01	7,40	20,30				
Inc. PT/AT	-9,85	0,000	18,88	0,00				
-2 log likehood	184,60	0,000						
Chi- squared	32,15							
AIC	204,6							

Rot Assets = Net sales/ Total Assets
Inc Assets = Rate of growth in total assets
CF/Sales = Cash Flow/ Net sales
PT/AT = Total debt/ Total Assets
Current Ratio = Current Assets/ Current liabilities
Inc. Rot Assets = Rate of growth of Net sales/ Total Assets
Inc Assets = Rate of growth in total assets
Inc. CF/Sales = Rate of growth of Cash Flow/ Net sales
Inc. PT/AT = Rate of growth of Total debt/ Total Assets
Inc. Current Ratio = Rate of growth of Current Assets/ Current liabilities

These studies only focus on determining which variables distinguish healthy companies of failed [5]. They used for made these research a static methodology with a static variable, but we understand that companies failure is a process. Therefore, we need a dynamic methodology and dynamic variables for the study of failure prediction.

Then in this research, we do not consider the variable to study as a dichotomous variable that distinguishes healthy entities failed as another research, because our goal is not to investigate those variables differ from one another better. Our main objective is to study the dynamic trajectory deterioration of a group failure companies along the pre-interruption of business activity period. We study the risk of companies failure once have been classified these companies in deterioration process. We also intend to identify which ratios allow us to better classify the companies between different processes of failure. We also study if the trend of these ratios provides more information on the risk of these companies.

One important conclusion is that there are different processes of business failure in our sample. We can verify, using cluster analysis (k-means cluster), different failure processes from the ratios described by literature on prediction of bankruptcy. And, we determine which companies is each of these processes fail.

Therefore, we can say that we anticipate the risk of failure for the processes of failure detected in the sample from [17] variables. And, we can say the same when we try to detect the risk of failure with [17]variables and their trends. But, we can not anticipate the risk of failure processes when we use only the trend of variables.

Another conclusion is that the best model which defines the risk of failure is when we include the [17] variables and their trends. Therefore, we can say that the trends of the variables alone do not define the risk of business failure. But they provide information about the risk of failure when included in the model along with the variables.

Finally, the most marked contributions of this work are, first, that the definition assigned to the dependent variable with the application of a dynamic approach allows us to study the risk of companies' failure throughout the period study. And, secondly, we have found that studying the risk of failure of the companies only with dynamic variables (variables trend) does not allow us to anticipate that risk of failure significantly. But we have seen that the trend of the variables provide information to the study if we include in the model along with the variables.

As limitations we should be noted that our study only focused on analyzing companies that have come disappearing, excluding research companies still active. This has been true for easy identification in the sample of companies subject to study different groups of companies that follow similar processes of deterioration. However, we would propose as a future line of work studying the failed companies classified by processes together with a sample of healthy companies.

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