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CHARACTERISING THE FINANCIAL BEHAVIOUR OF FAILED COMPANIES DURING THE COVID CRISIS

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Abstract

The Covid crisis have accentuated insolvency processes in companies which were apparently in a good financial condition. This study aims to characterise business failure processes pre and post COVID identifying more affected companies in function of different financial distress typologies. To do so, we propose the application of Big data algorithms, and in particular, qualitative comparative techniques, to identify the combination of financial ratios values, with statistically determines critical thresholds, to differentiate between failed and non failed companies. Based on this information, we distinguish different business failure processes. We apply this procedure to a sample of 30,101 Spanish companies located in Madrid during pre and post COVID periods. We characterise detected financial distress processes in function of companies' characteristics. We find structural changes in business failure processes as consequence of the Covid crisis where problems of solvency, because of high debt, and of liquidity play a fundamental in the quest to survive.

Keywords: business failure, clustering, symbolization process, COVID crisis

1. Introduction

The COVID-19 pandemic has caused financial distress in the economies taken as a whole, and with different intensity on their respective sectors. The coronavirus crisis has reduced companies' comercial transactions given the government regulations of social distancing to control the spread of this disease (Baqaee and Farhi, 2020). This situation has provoked an important drop in sales for many companies, as evidenced by, for example, Fasano et al. (2022). The effect of COVID on companies' performance and survival depends on a set of internal and external factors (Cook and Barrett, 2020; Ramelli and Wagner, 2020). Among the internal factors, companies' financial management is a key element to be considered. The well-known discussion about the optimal capital structure becomes a decisive factor, also during the COVID crisis (Fahlenbrach et al., 2020). Literature states that companies posit financial policies to guarantee trusted and cost-efficient access to capital market. The explanatory factors in the trade off between equity and debt are exposed in many studies, such as Leland (1998), which takes the work of Modigliani and Miller (1963) as a base and incorporate real life limitations that affect these authors' opening hypotheses. More recent theories have highlighted the importance of capital market imperfections in the choice of the enterprises' capital structure, as for example the information asymmetry problem in the pecking order theory, as proposed by Myers and Majluf (1984).

Since then, some studies have highlighted the importance of other factors which may affect companies' capital structure and their own survival. A number of these contributions highlight the concept of firms' financial flexibility indicating that some companies are interested in maintaining a financial slack, for the sake of prudence, because they are forced to, as external financing is problematic, or to finance future investment opportunities (Bigelli et al. 2014). But this financial flexibility or financial conservatism are not a generalized practice. Recent research has not found a general trend concluding that delevering is the main goal of an average company, which was the expected policy if financial flexibility was a critical driver of capital structure. Zheng (2022) explains this evidence by the negative incentives to reduce debt and keep large cash holdings, because, as Acharya et al. (2007) point out, cash can be considered as negative debt.

In this context, Fahlenbrach et al. (2020) highlight the relevance of firms' financial flexibility stating that companies with large cash flow and low debt positions are better able to face the unexpected revenue drop caused by the COVID crisis. Our study provides further evidence about the relevant role of firms' capital structure and financial condition, basing it on the well-known Altman's (1968) work, which measures each company's financial health by analyzing the values of related, but anyways different, concepts, such as liquidity, solvency, profitability, management, etc. At the end our study highlights the relevance of financial flexibility in the company's survival. In particular, our research questions are: which are the financial unhealthy conditions that make more probable the death of the company? Have these conditions changed during the COVID crisis? Is there any evidence that Altman values and model should be rethought?

With this purpose, we characterise business failure processes pre and post COVID regarding firms' financial characteristics. To do so, we apply big data algorithms implementing recursive procedures based on breaking structural tests and simbolization procedures to define the firms' financial positions during the period 2018-2020. Afterwards, in order to identify business failure processes, we develop specific algorithms based on the Chow test which overcome previous applied qualitative comparative techniques - as the fsQCA developed by Ragin (1987). Our methodological proposal exogenously determines the optimal thresholds in firms' financial ratios to define the different failure processes. After this, we categorise the different pre and post COVID business failure processes which are later characterised using multilogistic regressions in function of companies' internal characteristics.

In accordance with previous studies, we identify liquidity and financial flexibility/conservatism practices as a key element to survive during the pandemic (Fahlenbrach et al., 2020). The comparison between the failure processes before and after the COVID crisis exhibits a visible change. This study contributes to previous literature providing further understanding about most affected firms during the COVID crisis in function of their financial management. In this sense, despite the fact that the COVID shock had strong consequences on companies wealth (Wenzel et al., 2020), the mechanisms which cause this business failure are far to be understood. Our paper contributes to several strands of literatures.

Our study shows that some combinations of factors that measure a company's financial status have an impact when a company is exposed to an unexpected external shock. Second, our study contributes to the business failure literature, as COVID shock changes the rule of game of companies' survival/death dynamics comparing years before and after this crisis. Our proposal overcome previous literature identifying the predominant business failure processes during the COVID period and characterising each of them in function of companies' characteristics.

The study is structured as follows: the second section presents the main literature focused on business failure and the COVID shock. The third section shows the used database and sample to develop our study. The fourth section prosents the methodology including the specific algorithm we have designed to identify the different business failure processes. The next section presents our results, and we end this study with our conclusions, limitations and future research.

2. Literature

2.1 Business failure: a review in the COVID context

Literature examines explanatory business failure factors from deterministic and voluntaristic perspectives (Heracleous and Werres, 2016). The former is focused on external companies factors from which companies have scarce control (Amankwah-Amoah et al., 2021). These elements depend on general and sectoral environmental characteristics. Initial results in this context tended to examine different environmental factors- as for instance crisis or changes in government regulations- as the main determinants in business failure (Silverman et al., 1997). From a microterritorial perspective, we find studies which examine firms' surrounding characteristics as potential causal elements of business failure (Mate-Sanchez-Val et al., 2018). The latter-voluntaristic studies- highlights the existence of firms' characteristics such as financial management, investments and capabilities, as the main explanatory factors of business failure (Kücher et al., 2020). Thus, the basic difference between these theoretical bankgrounds- deterministic and voluntaristic- is the perspective from which the factors explanaining business failure are considered. Mostly of the recent studies have indicated the need of integrating a combination of external and internal factors to build a consistent business failure model (Amankwah-Amoah, 2016). Under this global approach, companies' bankruptcy could be explained by a disadjustment between companies characteristics and environments (Sabherwal et al., 2001). Over time, a sequence of firms' management decisions and negative external events would provoke a drop in competitiveness, rising debt level and finally reaching failure.

In this context, the COVID pandemic is considered as one of the most relevant exogenous shocks changing general market conditions (Wenzel et al., 2020). As consequence of this pandemic, governments' measures regarding health have adopted border closures and social distancing measures This crisis has provoked a collapse in demand in certain sectors, and a breaking in the supply of many activities. Thus, the unexpected change in the economic framework have disadjusted previous equilibrium between firms' internal characteristics and environmental conditions. The COVID crisis has caused demand and supply shocks resulting in situations where companies face difficulties to generate cash flows and pay suppliers (Cook and Barrett, 2020). Ramelli and Wagner (2020) find a negative relationship between returns and debt and a positive interaction between cash and stock returns. De Vito and Gómez (2020) examine how much time companies with reduced operating flexibility would be operative before they drain cash reserves. Ding et al. (2020) examine the relationship between best pre-COVID financial practices and the stock price results to COVID situation. Pagano et al. (2020) find that companies whose activities are less exposed to the social distance presented a lower decrease in their stock prices. Fahlenbrach et al. (2020) conclude that COVID shock have less impact on companies with more cash holdings. Differently as previous studies, we focus on the business failure process examining the typologies and differences in function of firms' characteristics during the COVID crisis.

3.- Database and sample

3.1 Sample

The sample is composed by a set of companies with financial statements from SABI (Iberian Balance Sheet Analysis Systems) database. These companies have available information over the period 2017-2020. We eliminate from our sample firms without financial information or with negative total assets (Zheng, 2021). After this process, we obtained a sample composed by 30101 observations. We classify a company as failed if it has filed for bankuptcy (Zorn et al., 2017), a definition widely applied in previous studies (Muñoz-Izquierdo et al., 2019 and Sanchez-Vidal et al. 2023). In our sample, we consider failed companies in a certain year those enterprises filing for bankrupctcy before the end of 2018, 2019 and 2020 respectively. In our database, there are 1421 failed companies along the three years of the sample period.

3.2 Variables

Five financial ratios were computed to measure firms' financial characteristics. We choose these ratios based on the widely applied Altman's Z score model (Altman, 1968). The Ratio 1 (R1) is defined as working capital to total assets. Working capital is the difference between a company's current assets and its current liabilities. This ratio is important from a short-term financial point of view and is a measure of the firm's liquidity, as a low value will probably mean that a company will have difficulty meeting its short-term financial obligations because current assets are insufficient. The Ratio 2 (R2) is computed as retained earnings to total assets. R2 indicates the amount of profit or loss retained in a company. If a firm has a low R2, it means that the firm has proportionally less internally generated funds to finance the corporation, and thus is a measure of solvency. A low value increases the probability that the company bankrupts. On the other hand, a high value indicates that the company has proportionally less need to resort to borrowing or to equity issues (external finance). The Ratio 3 (R3) is computed as earnings before interest and taxes (EBIT) to total assets. This ratio refers to a firm's capacity to generate profits from its own activity. It presents a company's ability to generate sufficient revenue, finance ongoing operations, meet payments and be profitable. The Ratio 4 (R4) calculated as total assets to total liabilities. A high ratio of total assets to total liabilities means that the firm does not finance its assets with a high proportion of liabilities. This ratio is another measure of solvency. The Ratio 5 (R5) defined as sales to total assets. This ratio defines the efficiency with which management uses assets to generate revenue and is a measure of rotation. A high R5 means that management needs a small investment to generate sales, which increases the overall profitability of the company.

All financial ratios were considered with one temporal lag for each analysed year. In the logistic analysis, we also consider firms' characteristics such as the *size* which is computed as the logarithm of firms' total assets. We consider the *Age* of the firm taking into account the years since its constitution. These two variables are usually an inverse proxy of information asymmetry problems, and thus, accounts for financial constraints problem (Bigelli et al. 2014). We use NACE (Nomenclature of Economic Activities) codes to identify firms' sectors. Table 1 provides the descriptive information of previous variables for the examined period.

Table 1. Descriptive statistics. Mean (sd.)

	2018	2019	2020
Failed companies	498	463	460
R1 (Working capital ratio)	0.0268 (0.992)	0.0043 (0.989)	-0.0350 (0.948)
R2 (Retained Earnings to total assets)	0.0320 (0.821)	0.0090 (0.931)	-0.1546 (0.648)
R3 (EBIT to total assets)	0.0495 (0.723)	0.0371 (0.897)	-0.1187 (0.657)
R4 (Total assets to total liabilities)	2.9187 (1.751)	3.4821 (1.508)	3.2900 (1.260)
R5 (Sales to total assets)	1.2973 (1.739)	1.4275 (1.952)	1.3365 (1.695)
Size (Logarithm of total assets)	6.658 (2.243)	6.673 (2.242)	6.701 (2.040)
Age (Log of firms' age)	21.41 (13.848)	20.59 (11.673)	20.74 (10.696)
	Number of cases		
Industry and agriculture activities	20	29	19
Building	40	35	51
Trade	104	85	72
Transport	21	13	10
Accommodation	30	33	38
Communications	36	29	33
Financial services	88	83	76
Proffesional and scientific activities	72	82	72
Others	34	45	57

The most relevant conclusions takable from these descriptive statistics are that that the number of companies that failed do not increase with respect to the previous years, that R1, R2, R3 fall in 2020 with respect to 2018 and 2019 and size and age do not seem determinant as there are no visible large changes, and that Industry does not show dramatic variations, except, perhaps, for a slight increase in Building, Accomodation, and a relative fall in Industry and agriculture activities and Trade.

4. Methodology

As difference from mostly of previous studies, we apply qualitative techniques. We propose an algorithm based on the idea of the fuzzy qualitative comparative analysis (fsQCA) proposed by Ragin (1987, 2000). This methodology allows us to identify the combination of financial conditions that may generate failure. This approach is more realistic than traditional applied techniques (such as multiple regression analysis) given that the failure process is defined by several combination of conditions, and so a very low level of profitability (R3) may have a much more negative impact in the group of companies with low capitalization (R2) than in the rest of enterprises with values of R2 positioned in higher centiles. This simultaneous and different impact of one factor on the company's survival depending on the other factors makes a standard OLS analysis (or, for example, a more specific quantile regression approach) unfeasible. fsQCA requires different steps: the first is to build a truth table where the selected variables- in our case five financial ratios- takes the values of 0 or 1 in function of some previously defined criterium, defined by the researcher. In this sense, the researcher considers whether the specific variable could cause failure if it takes a value higher than a certain threshold. As this could be a subjective step, we overcome this drawback by developing an algorithm based on the structural breaking Chow-tests along the distribution of each financial ratio. Based on the previous step, we design a symbolization procedure to categorize the five financial ratios (R_1, R_2, R_3, R_4, R_5) measured in each firm into a finite set of 32 symbols. Each of these symbols will have a meaning within the financial status of the firm. The symbols distribution will help us to analyze the time evolution of firm failure before and after the beginning of the COVID pandemic. We will then perform a cluster analysis of the failed firms, conducted through the symbols associated to their financial ratios in order to better understand different business failure processes, each one associated with a different combination of the Altman ratios representing the diverse factors previously mentioned. The section will end with a multinomial logistic model that explain the different types of firm failures (each cluster of symbols represent a different type of firm failure) as a function of a set of internal characteristics of the firm in the pre and post Covid-pandemic era.

4.1 Symbolization of financial ratios

Define the set $\Gamma = \{(0,0,0,0,0);\ (1,0,0,0,0); \ldots; (1,1,1,1,1)\}$ as the set of all vectors of length 5 with entries in the set $\{0,1\}$. Γ has cardinality 32 and its elements are called symbols. For each financial ratio R_i (i=1,2,…5) we consider the 9 deciles D_k^i (k=1,2,…9), that divide the distribution of R_i in 10 equal frequency intervals. With this decile we divide the sample of failes and non failed firms in two subsamples, the first one formed by those firms satisfying that $R_i \leq D_k^i$ and the second subsample formed by the remaining companies (i.e. those with $R_i > D_k^i$). For these two samples we perform a Chow-test with firm failure as the dependent variable (dichotomic) and the five financial ratios (R_1, R_2, R_3, R_4, R_5) as explanatory variables. Then we select the deciles that maximize the value of the Chow-test statistic, namely $\mathfrak{D}^i$. Notice that the subsamples determined by $\mathfrak{D}^i$ (i=1,2,3, 4 and 5) are those that maximize the difference between the linear regression models for dependent variable firm failure, estimated in the two samples. This procedure allows us to identify the threshold from which each of the financial ratios change the way in which they impact on the condition of business failure from an objective perspective. Thus, differently as fsQCA, we let the Chow test to objectively determine the thresholds and thus, we exogenously determine the value to build condition for each financial ratio.

Next, we define the symbolization map $S: \mathbb{R}^5 \to \Gamma$ defined by

$$S(x_1, x_2, x_3, x_4, x_5) = (\mathfrak{T}^1(x_1), \mathfrak{T}^2(x_2), \mathfrak{T}^3(x_3), \mathfrak{T}^4(x_4), \mathfrak{T}^5(x_5)) \quad (1)$$

where:

$$\mathfrak{T}^i(a) = \begin{cases} 1 & \text{if } a > \mathfrak{D}^i \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

is an indicator function taking the value 1 always its argument is greater than the corresponding decile $\mathfrak{D}^i$.

Therefore, with the symbolization map S, the vector formed by each company's combination of the five financial ratios into a symbol that summarizes that particular financial status. Notice that, given the noisy nature of the financial ratios, by analyzing the symbols distribution although we lose the numerical value of the ratios we gain in robustness when looking for different types of firm failures and their time evolution. Taking values associated with percentiles instead of the actual values has the advantage of controlling for outliers, which are typically numerous and influential in samples containing failed or near bankrupt enterprises (Sanchez-Vidal, 2014).

An example for the potential reader of what one specific symbol out of the 32 possible outcomes of the whole Γ means, let us take the particular combination: $(0,0,0,1,1)$. This symbol would characterize those companies with low values for R1, R2 and R3 and values above the threshold for R4 and R5, specifically meaning a value lower than that defined by the percentile 10 for the Working capital and the EBIT to total assets ratio, a value for the Retained Earnings ratio lower than that defined by the percentile 20, and values higher than the percentile 50 and 20 for the ratio of Total assets to total liabilities and Sales to total assets, respectively. As a matter of fact, the thresholds for all ratios but R4 are quite defining, as the companies below them represent very reduced subsamples.

4.2 Symbolic Clustering of Firm Failure

Each firm is associated with a symbol through the symbolization map S applied to its financial ratios. With the symbolic representation of the firms, we perform a cluster analysis applying k-means algorithm with the Hamming distance, which is the most adecuate distance in the symbols space. Remind that the Hamming distance between two vectors (or strings) of the same length is the number of entries of the vectors that are different from each other. Performing a cluster analysis in this way will results in clusters with similar financial characteristics that have been encapsulated in the symbols.

4.3 Multinomial Logistic Regressions

In assessing the degree of impact of firms' characteristics on business failure position, a multinomial logistic regression model where the dependent variable define business failure was defined. This variable takes the value of zero for no failed companies and values from 1 to 3 in function of the kind of business failure that characterise each of the studied companies. In this way, we consider a categorical dependent variable which is estimated through a multinomial logistic regression model, where the estimated probability (converted to odds) of each kind of business failure category, predicted by companies' characteristics, is the outcome of maximum likelihood function (Kennedy, 1998). Multinomial logistic regression is an adequate method for classification when the dependent variables present more than two choices. This procedure parts from the binary logistic regression (Hosmer and Lemeshow, 2000). In this model, the belonging to a kind of business failure process is a linear function of companies' characteristics. This model can be expressed as follows (3):

$$P_{ij} = \frac{\exp\left(x_i \beta_j\right)}{1 + \sum_{I=2}^{J} \exp\left(x_i \beta_j\right)} \tag{3}$$

where P_{ij} evaluates the associated probability with the choice of the jth alternative (one of firms' financial distress categories) by the ith company, x_{ij} represents the explanatory variables and β is the estimated coefficient (Kennedy, 1998). This specification is based on the log Weibull distribution which has the advantage that the cumulative density of the difference between any two random variables which have this distribution follows a logistic function (Kennedy, 1998). For instance, a company presents a specific financial failure process A if:

$$x_0 \beta_B + \varepsilon_B < x_0 \beta_A + \varepsilon_A \tag{4}$$

x_0 is a row vector of firms i's characteristics, then $(x_0 \beta_A + \varepsilon_A)$ is the probability of belonging to the kind of financial failure A and $(x_0 \beta_B + \varepsilon_B)$ is for the category B. ε_A and ε_B are independently drawn from a log Weibull distribution. Given a companies' characteristic, the probabilities of that company belonging to one of three different business failure categories is computed as follows:

$$\frac{probA}{probC} = e^{x\beta A} \text{ and } \frac{probB}{probC} = e^{x\beta B} \tag{5}$$

5 Results

This section shows the results of the business failure processes pre and post COVID for our sample of Spanish companies applying the methodology previously defined. Firstly, we apply a recursive algorithm based on the Chow-test to the pool of financial ratios from 2018 to 2020 to obtaine the firm symbolization as described in Subsection 4.2. Notice that we perform the symbolization procedure in the pool of the three years, for the symbols to have the same meaning and therefore, allowing for comparison of their distribution in the pre and post COVID pandemic. Secondly, we perform a 3-cluster analysis through the symbolic representation of the firm to identify different processes for bussines failure. Finaly, we characterise these failure processes as a function of business characteristics applying multinomial logistic regressions.

5.1 Pre and post Covid business failure processes

5.1.1 Symbolization and clustering process

After applying the proposed recursive algorithm to the pool of financial ratios from 2018 to 2020 for the whole sample, we obtain a different threshold for each of them. Table 2 shows these results:

Table 2. Thresholds based on the Chow test

Threshold	Percentile
$\mathfrak{D}^1$	10
$\mathfrak{D}^2$	20
$\mathfrak{D}^3$	10
$\mathfrak{D}^4$	50
$\mathfrak{D}^5$	20

Based on deciles values and applying the expression (2), we defined for each company a symbol composed by 5 elements representing of the five analysed financial ratios. Each element in the symbol will take the value of 0 or 1 depending on previously determined thresholds.

In order to characterize business failure processes of failed companies, starting with the symbolic representation of failed firms, we apply a k-means clustering algorithm using Hamming distance. Results of the cluster analysis are presented in Table 3. We find three different clusters for the pre and post COVID periods.

Table 3. Clustering processes based on the symbols of failed companies

Panel A. Clusters characterization

	Centroid (*)	Interpretation
Cluster 1	1 0 1 0 1	Cluster 1 is characterized by companies not capitalized (low o null proportion of retained earnings) and with low solvency (its assets are proportionally more financed with debt).
Cluster 2	0 1 1 0 1	Companies with low liquidity and solvency (mainly financed with debt).
Cluster 3	0 0 0 0 1	Companies with low liquidity, low solvency (low capitalization from reserves), low current profitability and low solvency (caused by high debt).

(*) We find similar centroids for each year of the analysed period 2018-2020.

Panel B. Percentaje of companies in each cluster in the analized period			
	Cluster 1	Cluster 2	Cluster 3
Pre-COVID	59%	27%	14%
Post-COVID	26%	65%	8%

Panel A of Table 3 includes the interpretation of the characteristics of each Cluster. Panel B shows the distribution of clusters before and after the pandemic. Taking an overall look at the Clusters, the three have in common that R5 is not determining. This is logical, as rotation is quite dependent on the sector (industrial companies, for example, tend to have high proportion of fixed assets, high margins and low rotation, and on the other hand, commercial companies are usually characterized by low margins and high rotation, and what this means is that it does not matter the sector, but any company can file for bankruptcy. When we compare the changing importance of the different Clusters before and after COVID, we conclude that once the COVID crisis comes into play, Clusters 1 and 3 are less important, as the weight of the Cluster 2 rises in the post COVID period. This implies that problems with liquidity (R1) and solvency, because of high debt (R4) gain protagonism (although the other ratio related to retained earnings and solvency too (R2) is now not that important), and that current profitability is now less determining.

This result highlights the relevance of firms' liquidity. Regarding solvency, the results are ambiguous, but taking into account that the ratio R2 seems more inertial, as reserves are the product of previous profitabilities and past policies of profit retention/dividend distribution, and thus, change slowly, we can conclude that highly levered companies suffered proportionally more from the pandemic as the crisis seemed to affect more companies with higher debt, and which could possibly not draw upon more debt to overcome the difficult 2020. This diminished capacity response in the short term is a lack of financial flexibility, and logically, those companies which applied preventive financial policies, keeping higher level of corporate cash holdings and low debt, were able to face potential credit rigidities and the lack of accessibility to external fundings (Neukirchen et al., 2022). This scarce financial flexibility could plausibly be the cause of not being able to meet the companies' short-term payments, spawning severe problems of liquidity.

5.2 The multinomial logistic regression

In order to characterise each cluster in function of firms' characteristics, we estimate a multilogistic regression for failed companies in each year. The dependent variable FrC takes the value 1 if the company belongs to the Cluster 1, 2 if the company belongs to the Cluster 2 and 3 in case the company is in Cluster 3. The explanatory variables are size, age and the industry the company belongs to. In order to run the analysis, cluster 1 (FrC=1) is left as the base category.

Table 2. Multilogistic regression estimation results, where Cluster 1: 1 0 1 0 1 is left as the base category.

	Pre Covid		Post COVID	
	Cluster2 (0 1 1 0 1)	Cluster 3 (0 0 0 0 1)	Cluster2 (0 1 1 0 1)	Cluster 3 (0 0 0 0 1)
Size	-0.0947** (0.064)	-0.2654*** (0.002)	-0.0015 (0.976)	-0.1988*** (0.047)
Age	0.0315 (0.801)	-0.2134 (0.374)	0.3733** (0.010)	-0.1156 (0.646)
Industry	0.9183 (0.094)	1.4999* (0.086)	0.1323 (0.833)	0.1330 (0.908)
Building	0.4665 (0.243)	0.1956 (0.808)	0.4112 (0.405)	0.3848 (0.687)
Trade	0.7743** (0.026)	1.1176* (0.074)	-0.1779 (0.368)	0.7533* (0.050)
Accomm	0.4487 (0.355)	1.0422 (0.198)	0.0209 (0.963)	0.9557* (0.086)
Transport	0.7325* (0.091)	0.0952 (0.935)	-0.7097 (0.313)	-0.9568*** (0.000)
Communications	0.6868 (0.134)	1.4996** (0.040)	-0.2262 (0.682)	0.5782 (0.557)
Financial Activities	1.0058*** (0.005)	1.1668** (0.065)	-0.4646* (0.082)	0.6101 (0.310)
Scientific and profess. activi.	0.5342 (0.370)	0.8906 (0.173)	0.0780 (0.833)	0.0789 (0.911)
Other activities	0.3802 (0.439)	1.0980* (0.097)	-0.9250** (0.013)	0.2719 (0.746)

*In parentheses the p-value. *** significant at 1%** significant at 5% * significant at 10%. We include those representative sectors with observations for each cluster.*

Our results indicate that during the pre COVID phase, one-unit risen in the companies' size is related to a decrease in the log odds of being in Cluster 2 vs being in the reference cluster in the amount of 0.0947. The same happens with the Cluster 3. Thus, as companies' size increases the probability of being in Clusters 2 and 3 is lower in comparison with the Cluster 1. This result is also significant in the post COVID period, but only for Cluster 3. Thus, an increase in one unit of companies' size will drop the probability of being in Cluster 3 in comparison with Cluster 1. Regarding firms' age, we find that this variable is not significant during the pre-COVID period but becomes significant for the post-COVID period. The probability of a company of being in the

Cluster 2 rises as the firm gets older, probably old companies which are not as capitalized as their counterparts, and which the pandemic caught wrong-footed, increased their probabilities of failure. Regarding differences between sectors, we find that companies in the Trade and Financial sector present high probability of being in Clusters 2 and 3 during the pre-COVID period. During the post COVID period, we find lower probability of being in Cluster 2 of companies in the sectors of financial activities and other activities during the post-COVID period.

6. Discussion and conclusions

In this paper, we examine the impact of the COVID crisis on firms' business failure. The most visible change is a break in the business failure processes, as some factors which were determining before the pandemic turn irrelevant, and others become crucial when they were not before. Liquidity and solvency, linked to financial flexibility, seemed critical once the pandemic made a start. This result coincides with previous literature bringing firms' financial flexibility out (Neukirchen et al., 2022). We find that the positive effects of financial flexibility during the post COVID period is explained by more capacity to get external financial resources (Zheng, 2022), of which post COVID companies seem more dependent. In addition, more mature companies during the post COVID period have more probability of going bankrupt. Finally, we find interesting results when we compare failed pre and post COVID companies in relation to their productive activity.

This paper strenghs the relevance of financial flexibility which allow companies to be proportionally more financially independent from external resources. This paper provides additional light to the question about the trade off between equity and debt in the context of the presence of an unexpected external shock, which seemed to intensify the disadvantages of debt during the pandemic. Our results provide further evidence about the relevance of financial flexibility during the COVID period (Faulender, 2021) and the importance of the companies' financial policy. The restarted adequate equilibrium between equity and debt after the pandemic seem to depend on firms' internal characteristics too.

This study opens new possibilities in the analysis of business failure, in which the pandemic has changed the rules of game. The novelty of this study is both the definition of the deciles that constitute a threshold of the different Altman ratios and the analysis of the diverse combinations of these ratios, through a symbolic analysis. This study opens the way to new approaches for prediction of business failure and new methods of classification. One of the limitations of this study, which in turn entails future research, is the generability of the results once the pandemic has been overcome. Further parallel research should try to assess whether the Altman model is still valid and try to identify the new values of the Altman analysis in case they have changed. Finally, this study is exclusively based on firms' internal characteristics. The consideration of firms' environment factors in this context is challenge which will be proposed in our coming studies.

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