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The influence of the vulnerability of sectors on their survival and probability of insolvency: the case of small and medium entities in Spain

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ABSTRACT

This paper looks at a sample of small and medium entities in Spain and analyzes the effect of the vulnerability of sectors to insolvency on their survival and the probability that they will go bankrupt. We collected data from solvent and insolvent firms in Spain over the period 2012-2016, and grouped them according to the percentage of insolvencies by sector (highest, lowest, and a reference group). The results show that no differences in the endurance of the firms emerge among the groups, while some variables appear to be relevant when the logit analysis is applied. Survival depends on liquidity and size in all industries, but profitability and turnover are also essential for the group with the highest levels of insolvency. The probability of bankruptcy is mainly explained by turnover and short-term solvency. Size and turnover have negative effects on bankruptcy. Age is also a common factor, but with a different interpretation for each technique. The main contribution of this paper is the analysis of insolvency in the two dimensions of survival and probability according to the sectorial insolvency rate.

Keywords: insolvency, bankrutpcy, survival, logit, Spain.
JEL classification: G33; M41; M21.
MSC2010: 62J12; 62N02; 62N03.

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La influencia de la vulnerabilidad de los sectores en su supervivencia y probabilidad de insolvencia: el caso de las pequeñas y medianas entidades en España

RESUMEN

Este artículo analiza la vulnerabilidad sectorial a la insolvencia basándose en el análisis de supervivencia y la probabilidad de la misma en una muestra de pequeñas y medianas empresas en España. Se han recogido datos de empresas solventes e insolventes para el período 2012-2016 y han sido agrupadas por el porcentaje de insolvencias por sectores (alto, bajo y un grupo de referencia). Los resultados muestran que no hay diferencias en la duración de las empresas entre los grupos y algunas variables parecen ser relevantes cuando se aplica el análisis logístico. La supervivencia depende de la liquidez y el tamaño en todos los sectores, pero la rentabilidad y la rotación son también esenciales para el grupo con más altos niveles de insolvencia. La probabilidad de quiebra se explica principalmente por la rotación y la solvencia a corto plazo. El tamaño y la rotación tiene efectos negativos sobre la quiebra. La edad del negocio es también un factor común, pero con diferentes interpretaciones para cada técnica. La principal contribución del artículo reside en el análisis de la insolvencia en dos dimensiones: supervivencia y probabilidad de acuerdo con la tasa de insolvencia sectorial.

Palabras clave: insolvencia, quiebra, supervivencia, logit, España.
Clasificación JEL: G33; M41; M21.
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1. Introduction.

Credit risk and bankruptcy prediction research has been one of the main research topics in accounting and finance, and continues to attract the interest of academics and other practitioners.

The history and development of insolvency prediction models started in the 1960s with the well-known works of Beaver (1966) and Altman (1968). Since then, an increasing number of studies of insolvency prediction models have appeared and this field of research has widened the scope of analysis and used various techniques (multiple discriminant analysis, logit, iterative partitioning, neuronal networks, among others).

Industry-wide distress can affect the insolvency of firms: firstly, by lowering the economic worth of the assets of the firm that has defaulted; and secondly, because the prices at which assets of insolvent firms can be sold depends on the financial condition of peer firms (competitors) (Shleifer & Vishny, 1992). If default intensities are different across industries with otherwise identical firm-specific characteristics, it is of interest to investigate the determinants behind the effect on the industry.

The main objectives of this study are to analyze how the vulnerability of sectors (measured as the number of insolvencies over the number of existing firms) influences their survival and the probability of insolvency. Further, we wish to compare the explanatory variables from two points of view: technique and the criteria employed to create the groups. We try to answer the question of whether the explanatory variables are different if the sample used shows a high (or low) percentage of insolvent firms. At the same time, we seek to compare both techniques considering that they are different.

The contribution of this paper is twofold. On the one hand, it allows us to evaluate whether the risk to insolvency determines the survival of firms and the probability of bankruptcy. To our knowledge, this is the first study that compares samples in different sectors grouping them according to the risk of insolvency. On the other hand, it sheds light on the role that the explanatory variables play in these samples and on the results of the techniques.

The variables time and the probability differ according to the sector that is in distress, so the industry effect is significant for explaining survival. Moreover, the investigation of the outcome of insolvencies gives some additional insights: liquidity, profitability and size are determinants of the survival of firms. Additional factors such as return, short-term liquidity and turnover determine the probability.

The structure of the paper responds to the aim of the research. The first part is devoted to a revision of the literature, especially those contributions that consider sector variables. The following sections explain the process of sample selection and the choice of variables in the articles on this topic. The empirical sections analyze the data: firstly, in a descriptive way, secondly, through the survival models; and, finally, through the logit model.

2. Background.

The role of sector in insolvency probability has been extensively studied in the literature. The works of Edminster (1972), Platt and Platt (1991) and Mensah (1984) used variables adjusted by sector in order to compare the accuracy of the models with and without these adjustments and found that those with adjusted variables were better.

Subsequently, the industry effect on insolvency prediction has been analyzed as part of the explanatory variables and in order to test hypotheses. Lang and Stulz (1992), Shleifer and Vishny (1992), Opler and Titman (1994), Maksimovic and Philips (1997), and Berkovitch and Israel (1998) support the importance of industry effects on bankruptcy. A substantial body of research built models for a particular industry: banking (Brown & Dinç 2011; Momparler, Carmona & Climent, 2016; Iannota, Nocera & Sironi, 2007; Rumler & Waschiczek, 2016; Anchor, 2017; Petria, 2016; Bhimani, Gulamhussen & Lopes, 2013; Soedarmono, Machrouh & Tarazi, 2013); transport (Brozyna, Mentel & Pisula, 2016); petroleum (Karan, Arslan & Alatli, 2009); technology (Hsu, 2011; Huang, 2015), among others.

Although most of researchers have detected some influence of market structure on insolvency, Kennedy (2000) states that this effect is small. Chava and Jarrow (2004) highlight the reasons why the inclusion of sector variables can improve the models:

> First, different industries face different levels of competition and, therefore, the likelihood of bankruptcy can differ for firms in different industries with otherwise identical balance sheets. Second, different industries may have different accounting conventions, again implying that the likelihood of bankruptcy can differ for firms in different industries with otherwise identical balance sheets. (p. 538)

The significance of industry as an important determinant of default risk is also put forward by Aertz and Pope (2013) who conclude that the changes in default risk always depend on global (but not national) factors and industry effects.

A number of studies compare the incidence of bankruptcy in different industries. For example, Berkovitch and Israel (1998) found that the proportion of firms that filed for bankruptcy is higher in mature industries as opposed to growth industries; Bunn and Redwood (2003), incorporating the macroeconomic effects into their model, showed that service firms have a lower probability of insolvency than the manufacturing sector.

Some authors include sectorial variables in a general model. For instance, Bhimani, Gulamhussen and Lopes (2010) revealed that industry and geographical variables influenced default for a sample of privately held Portuguese firms. Kaplan and Milton (2012) also applied three sectorial variables; and Huang and Lee (2013) used interaction terms between industry, firm size and competition intensity. Bhimani, Gulamhussen and Lopes (2013), using bank loan information to predict the timing of defaults, found that the incremental predictive ability of non-financial information surpassed that of macroeconomic and financial accounting information in the baseline, industry, and in- and out-of-the sample models. Laguillo (2016) also pointed out that the inclusion of qualitative sectorial variables improves the models and that general models (mixture of different sectors) are better than models focused on one industry.

The effect of concentration in industry has been the focus of several contributions. In general, the main conclusion is that industries that are more concentrated exhibit a higher probability of insolvency (Chiu, Pena & Wang, 2013; Zhang, Altman & Yen, 2010). Geopalan and Xie (2011) concluded that industries are more prone to distress if they have greater conglomeration. Along the same lines, Zhang (2013) found that competitors are affected more adversely if they are in industries that are more concentrated. Closely related to this, customer concentration (Irvine, Park & Yıldızhan, 2015; Chiu, Pena & Wang, 2013; Huang & Lee, 2013) produced contradictory results as Chiu, Pena and Wang (2013) pointed out that it did not affect failure probabilities (while Irvine, Park, & Yildizhan (2015) provided confirmatory evidence). In a similar way, Maksimovic and Philips (1997) presented evidence that incidence of bankruptcy depends on industry demand conditions. The other side of the coin, competition, is another issue that has been studied. For example, Kanatas and Qui (2004) concluded that takeovers of distressed firms are related to the nature of product market competition. Soedarmono, Machrouh and Tarazi (2013) found that a higher degree of market power in the banking market is associated with higher insolvency risk of banks.

2.1. Insolvency models for Spain.

In Spain different authors have extensively studied insolvency prediction over the last 30 years. Some authors have built a general model (Gabás, 1990; Gallego, Gómez & Yañez, 1997; Liazarraga & Archel, 1998, among others); others have focused on a single sector: banks (Laffarga, Martín, & Vázquez, 1985, 1986, 1991, among others); insurance (López-Herrera Moreno, & Rodríguez, 1994, Arellano, Gil, & Martínez 2003); manufacturing (García, Calvo & Arqués, 1997); other industries (textiles, Somoza 2001; hospitals, Bernal-Delgado, Campillo-Artero, & García-Armesto, 2014). In some cases, the focus of interest has been the legal form of the entity (cooperatives, Masa, Iturrioz & Martín, 2016; Iturrioz & Martin 2013 in others), the comparison of different ways of bankruptcy resolution (López-Gutiérrez, Torre-Olmo, & Sanfilippo-Azofra, 2011).

The use of different variables has also been analysed, especially cash flow (Gabás, 1990; Lizarraga, 1997; Lizarraga & Archel, 1998; De Llano, Piñeiro & Rodríguez, 2016; Rodríguez-López, Piñeiro & de Llano, 2014; Rodríguez-Masero & López-Manjón, 2016). A wide variety of techniques has been applied: for example, artificial neuronal nets (Serrano & Martín, 1993) and iterative partitions (Gabás, 1990). Other investigations have focused on SMEs (Small and Medium Entities) (Van Hemmen, 1997; Lizarraga, 1997; Pozuelo, Labatut, & Veres, 2013; Miranda, De la Torre & Martínez, 2008). To our knowledge, however, the effect of the vulnerability of industry to insolvency has not been analyzed and this is the main contribution of this paper.

3. Survival analysis.

Survival analysis models the probability of a change in a dependent variable *Y* from an origin state *j* to a destination state *K* due to casual factors (Bloosfeld & Rohwer, 1995). The event failure time represents the duration of time until the dependent variable changes from state *j* to state *k*. The focus is on the occurrence and timing of financial distress (LeClere, 2000, 2005).

The survival function gives the probability that a firm survives longer than some specified time *t*, namely, it gives the probability that the random variable *T* exceeds the specified time of study *P(T>t)* (1):

$$S(t) = \mathrm{P}(T > t) \tag{1}$$

It represents the probability that *T* is greater than a value *t* and indicates the survival time is longer than *t*.

The probability density function is defined as (2):

$$f(t) = \lim_{\Delta t \to 0} \left(\frac{\mathrm{P(t{\leq}T{<}t{+}\Delta t} \mid T \geq t}{\Delta \mathrm{t}} \right) \tag{2}$$

This function "gives insight into conditional failure rates; identifies the specific model form and mathematical model for survival analysis, and it is usually written in terms of this function" (Kleinbaum & Klein, 2012, p. 45).

The Kaplan-Meier survival curves plot survival data. This survivor function, denoted by *S(t),*gives the probability that the random variable *T* exceeds the specified time. Theoretically, the survival function is a smooth curve which begins at *S(t)=1* at *t=0* and heads downward towards zero as *t* increases towards infinity.

In this study, the Cox PH model has been used (equation 3). This model provides an expression for the hazard at the time *t* for an individual with a given specification of a set of covariates. This is a semi-parametric model in which the hazard rate at time t is the product of two functions, a baseline hazard function that is a function of t, but does not involve the predictors, and the exponential expression (3) that involves a set of covariates.

$$h(t, \mathrm{X}) = h_o(t)\exp(\beta_1 X_1 + \cdots + \beta_p X_p) \tag{3}$$

where $X_1, X_2, \ldots, X_p$ are the vector of covariates.

The application of survival analysis to insolvency started with the works of Lane, Looney and Wansley (1986) in an accounting-related area and Kim, Anderson, Amburgey and Hickman (1995) in insolvencies. Since then, a great number of studies have applied it using this technique with different objectives.

4. Sample.

Given that the aim of this study is to analyze the influence of sector vulnerability on failure, the first step has been to select the sectors in which the number of insolvencies was the highest and the lowest.

According to statistics by the National Statistics Institute (Table 1), we can divide the industry population into three groups:

- those with the highest level of insolvencies: construction of buildings, wholesale trade (except of motor vehicles and motorcycles), and retail trade (except of motor vehicles and motorcycles).
- those with the lowest level of insolvencies: manufacture of computers, electronic and optical products; manufacture of electrical equipment; manufacture of machinery and equipment; manufacture of motor vehicles, trailers and semi-trailers; manufacture of other transport equipment; manufacture of furniture; other manufacturing; agriculture; energy.
- a reference group (that excludes the previous sectors). This is a sample of firms that did not belong to any of the previous sectors (the highest and the lowest levels of insolvencies).

Table 1. National statistics of the number of insolvencies by sector.

INDUSTRIES (by year)	2016	%	2015	%	2014	%	2013	%	2012	%
-Agriculture and fishing	44	1	70	1	57	1	83	1	71	1
-Manufacturing and energy	528	8	642	8	1023	10	1575	11	1531	11
▪ Manufacturing: intermediate goods	207	3	218	3	365	4	623	4	597	4
▪ Manufacturing: capital goods	104	2	139	2	241	2	385	3	448	3
▪ Manufacturing: durable consumer goods	42	1	51	1	90	1	141	1	150	1
▪ Manufacturing: non-durable consumer goods	147	2	193	2	263	3	379	3	318	2
▪ Energy	28	0	41	1	64	1	47	0	18	0
-Building	782	12	1031	13	1511	15	2430	16	2487	18
▪ Houses	522	8	723	9	1024	10	1591	11	1633	12
▪ Other	260	4	308	4	487	5	839	6	854	6
-Commerce	895	14	1100	14	1272	12	1687	11	1505	11
-Wholesale trade	817	13	987	13	1115	11	1449	10	1330	10
-Retail	78	1	113	1	157	2	238	2	175	1

-Transportation and logistics	148	2	172	2	253	2	316	2	362	3
-Catering	277	4	302	4	369	4	400	3	277	2
-Information and communications	138	2	187	2	210	2	217	1	152	1
-Real estate, financials and insurance	174	3	172	2	253	2	373	3	268	2
-Professional, scientific and technical activities	349	5	390	5	425	4	573	4	355	3
-Administrative activities and auxiliary services.	230	4	222	3	284	3	455	3	287	2
-Other services	321	5	319	4	340	3	360	2	302	2
-No classification	411	6	490	6	567	5	674	5	498	4
TOTAL	6502	100	7870	100	10370	100	14835	100	13618	100

Source: Instituto Nacional de Estadística (INE), 2017.

The next step was to look for the size of these firms. The Spanish statistics only depict turnover as an approximation to size. As we can see, bankruptcies were focused on the lowest values of turnover (Table 2).

Table 2. National statistics of the number of insolvent firms by turnover.

Turnover (millions of euros)	2016	%	2015	%	2014	%	2013	%	2012	%
Below 0.25	1618	38	1864	37	2319	35	2806	31	2322	26
-From 0.5 to 1	484	11	593	12	680	10	1114	12	1218	13
-From 0.25 to 0.5	514	12	589	12	724	11	987	11	1085	12
-From 1 to 2	375	9	406	8	522	8	975	11	1060	12
Below 2										
-From 2 to 5	256	6	316	6	404	6	809	9	949	10
-From 5 to 10	90	2	118	2	170	3	342	4	375	4
More than 10	72	2	87	2	126	2	293	3	306	3
No classification	888	21	1124	22	1619	25	1817	20	1724	19
TOTAL	4297	100	5097	100	6564	100	9143	100	9039	100

Source: Instituto Nacional de Estadística (INE), 2017.

The sample is built by classifying the firms into one of the three groups and into the lowest of turnover values.

The pairing process consisted of matching one bankrupt firm with another in the same group that was solvent and had a similar turnover. The number of firms analyzed was 1164 for the sectors with the highest incidence of bankruptcy; 440 for those with the lowest rates of bankruptcy; and 2652 in the reference group (Table 3).

Table 3. Impairment process and total sample.

Number of firms with the lowest turnover	*INSOLVENT GROUP*						*SOLVENT GROUP*	*TOTAL*
	2016	2015	2014	2013	2012	TOTAL	TOTAL	
Highest number of insolvencies	147	95	82	54	17	582	582	1164
Lowest rates of insolvencies	56	32	24	16	10	220	220	440
Reference group	351	206	189	85	21	1281	1281	2562
Total	554	333	295	155	48	2083	2083	4166

Source: Own elaboration.

Once the selection of the sample was made, we collected the financial variables in the SABI (Sistema de Análisis de Balances Ibéricos) database (*Bureau van Dijk* for Spain and Portugal) for the 10 years 2006-2016 in order to go back in time. We consider that the last year (year -1) was about 12-13 months before the legal proceedings in order to avoid the last variables being biased by the event (as Ohlson, 1980, pointed out). In some cases, this last year was not available.

5. Variables.

The variables were chosen according to the previous literature and respond~~s~~ to the main features of a firm: solvency, leverage, profitability, liquidity and turnover were represented by one or more ratios as continuous variables (Table 4). When average measures were calculated, we considered two consecutive years.

The categorical variables are sector and age. Sector takes the value 0 if the firm belongs to one (or more) industries with the highest number of insolvencies and 1 if the firm operates in one (or more) industries with the lowest number of insolvencies. If the firm belongs to one (or more) industries in the reference group, then the variable is 2.

Table 4. Selected ratios according to previous literature.

Ratio	Calculation	Characteristic	Authors	Expected sign (insolvency)
WORKING CAPITAL/ TOTAL ASSETS (WC_TA)	(current assets-current liabilities)/ total assets	SOLVENCY	Chava & Jarrow (2004) Zhang, Altman & Yen (2010)	-
TOTAL LIABILITIES/ TOTAL ASSETS (TL_TA)	(long-term debt + short-term debt)/total assets	LEVERAGE	Chava & Jarrow (2004) Hernández & Wilson (2013), Irvine, Park, & Yıldızhan, (2015) (as market value of total assets), Huang & Lee (2013), Chiu, Pena, & Wang(2013)	+

SECTOR	0: if the firm belongs to the sectors with the highest percentage of bankruptcies. 1: if the firm belongs to the sector with the lowest percentage of bankruptcies. 2: if the firm belongs to other sectors.	INDUSTRY	Bhimani, Gulamhussen, & Lopes (2013), Huang & Lee (2013)	+/-
RETURN ON INVESTMENT (ROI)	(net income+ financial expenses x (1- (tax income/earnings before tax))/average total assets	PROFITABILITY	Chava & Jarrow (2004) James & Kizilaslan (2014) Chiu, Pena & Wang (2013), Shingal & Zu (2013), Huang & Lee (2013)	-
RETURN ON EQUITY (ROE)	Net income / average of equity minus net income	PROFITABILITY	James & Kizilaslan (2014)	-
RELATIVE SIZE	Log (total assets)	SIZE	Chiu, Pena & Wang.(2013), Hernández & Wilson (2013), Huang & Lee (2013), James & Kizilaslan (2014)	-
EBITDA/ INTEREST EXPENSES (EBITDA_INT)	Earnings before interest and taxes (EBITDA)/ financial expenses	FINANCIAL COVERAGE	Hernández & Wilson (2013), Zhang (2010)	-
EBITDA/TOTAL ASSETS (EBITDA_TA)	Earnings before interest and taxes/ total assets	PROFITABILITY	James & Kizilaslan (2014)	-
CASH AND SHORT-TERM ASSETS TO MARKET VALUE OF ASSETS (CASH_TA)	(Cash+ short-term assets) / total assets	LIQUIDITY	Irvine, Park, & Yıldızhan (2015), Chiu, Pena & Wang (2013)	-
ASSET TURNOVER (TURNV)	Sales / total assets	TURNOVER	Chava & Jarrow (2004), Irvine, Park, & Yıldızhan (2015)	+/-
AGE	0= if the firm operates in the sector for less than 20 years. 1= if the firm operates in the sector for more than 20 years.	AGE	Bhimani, Gulamhussen, & Lopes (2013), Lukason, Laitinen, & Suvas (2016)	-

Source: Own elaboration.

Some other variables were rejected as the sample consisted of privately held companies not trading on the stock market (for instance, among others, market to book ratio).

In the case of age, the binary variable is 0 if the firm has less than 20 years of activity and 1 if greater. This choice responds to the fact that the number of insolvencies drops after 20 years of activity (Table 5): namely, that the insolvency focuses on the youngest firms. It is reasonable to think that the number of years is a positive factor in relation to survival, in line with previous literature.

Table 5. Insolvency rates according to years of activity.

Number of years of activity	2016	%	2015	%	2014	%	2013	%	2012	%
% Below 4	768	18	802	16	803	12	1074	12	848	10
From 5 to 8	767	18	892	18	1272	19	1892	21	1885	22
From 9 to 12	830	19	1001	20	1249	19	1598	17	1354	16
From 13 to 16	521	12	725	14	924	14	1233	13	1063	12
From 17 to 19	330	8	387	8	560	9	797	9	1302	15
Below 20 years	3216	75	3807	75	4808	73	6594	72	6452	75
20 or more	959	22	1137	22	1579	24	2310	25	1945	23
No classification	122	3	153	3	177	3	239	3	184	2
TOTAL	4297	100	5097	100	6564	100	9143	100	8581	100

Source: Own elaboration.

6. Descriptive results.

The descriptive analysis has been made according to the final situation of the firm (solvent *vs.* bankrupt), sector and age. It is based on the average of available ratios for each firm and winsorizing each variable at 99% (in general, most of the firms for the solvent group showed available data for 10 years; however, most of the firms for the insolvent group only showed available data for 5 years).

The solvent firms (Table 6) exhibit the highest values of short-term solvency (WC_TA, .0890877), return (ROI, .0681726; ROE, .3873298, and EBITDA_TA .0307027), asset size (LOGTA, 7.555586); liquidity (CASH_TA, .3877141); turnover (TURNV, 1.503377), and financial coverage (EBITDA_INT, 1987.07). Insolvent firms show a higher level of indebtedness (TD_TA, 1.039512).

Table 6. Descriptive analysis according to financial situation.

	Solvent group				***Insolvent group***			
	Obs	Mean	Median	Std. Dev.	Obs	Mean	Median	Std. Dev.
WC_TA	1974	.0890877	.1607994	.680998	1987	-.2036494	-.0020111	.9817387
TD_TA	1786	.6959119	.6961837	.464377	1798	1.039512	.9014694	.7101794
ROI	1887	.0681726	.0488757	.1344187	1663	-.0112375	.0131441	.1355322
LOGTA	1974	7.555586	7.170401	1.828494	1986	6.512614	6.378255	1.640026
EBITDA_INT	1949	1987.07	8.056549	13643.09	1958	8.815107	.0697433	5921.84
EBITDA_TA	1973	.0307027	.05134	.2261069	1982	-.0967396	-.0046522	.3283919

CASH_TA	1969	.3877141	.3022612	.3271098	1967	.2387294	.1433063	.2602881
TURNV	1974	1.503377	1.058445	1.711.722	1968	1.304126	.9091041	1.523722
ROE	1968	3873298	.0858454	3.822821	1980	-.5158398	-.0553598	3.819109

Source: Own elaboration.

The next step was to compare the three groups: the group with the highest number of insolvencies (Table 7) also exhibits the highest values of short-term solvency (working capital to total assets, .005113), indebtedness (.9009945), return (ROI, .0320139; EBITDA_TA, -.0178969), and turnover (1.567199). In contrast, the group with the lowest number of insolvencies (sector 1) exhibits the highest asset (LOGTA, 7.513352); ROE (.2194906), and EBITDA_INT (1118.37). The reference group (number 2) shows the best liquidity (CASH_TA: .3195494).

Table 7. Descriptive analysis by group.

	Group 0				*Group 1*				*Group 2*			
	Obs	Mean	Median	Std. Dev.	Obs	Mean	Median	Std. Dev.	Obs	Mean	Median	Std. Dev.
WC_TA	1150	.005113	.1973231	1.008429	228	.0016733	.0978015	.5859262	2583	-.0910003	.0525476	.8016716
TD_TA	1036	.9009945	0.8361676	.6324804	215	.7850464	.7481284	.6099476	2333	.861434	.796826	.6214708
ROI	1052	.0320139	0.028816	.1193275	192	.0197147	.0240562	.1314949	2306	.0314353	.031377	.1500351
LOGTA	1150	7.143599	6.899671	1.85443	227	7.513352	7.423715	1.614065	2583	6.940809	6.686921	1.801965
EBITDA_INT	1133	771.3991	1.44972	10488.39	227	738.2079	1.282386	7383.131	2547	1118.371	2.174304	10820.3
EBITDA_TA	1147	-.0178969	0.0200264	.2526167	226	-.032581	.0126915	.2455823	2582	-.0399963	.0226685	.3071026
CASH_TA	1146	.3130887	0.0753719	.3256681	226	.2427676	.157439	.2260284	2564	.3195494	.2295321	.3005116
TURNV	1134	1.567199	1.04555	1.81027	225	.697641	.4760755	.7761402	2583	1.393733	1.005059	1.573926
ROE	1146	-.1554564	0.0254128	4.149641	225	.2194906	-.0015	2.688422	2577	-.0505744	.028012	3.792574

Group 0: the industries with the highest level of insolvencies.
Group 1: the industries with the lowest level of insolvencies.
Group 2: reference group.

Source: Own elaboration.

Regarding the effect of age, the firms with fewer than 20 years of activity (Table 8) show the highest values of indebtedness (TD_TA: .9742124), liquidity (CASH_TA: .3514962), and turnover (TURNV: 1.710523). In comparison, the group of companies with more than 20 years of activity (age=1) show the highest short-term solvency (working capital to total asset, .046256), return (ROI, .0309879; EBITDA_TA, .0011951, ROE, -.0278554), assets (LOGTA: 7.650233), and interest coverage (EBITDA_INT, 1219.338). The analysis of the medians gives a similar picture of the group profiles with some small differences.

Table 8. Descriptive analysis according to age.

	Age 0				*Age 1*			
Variable	Obs	Mean	Median	Std. Dev.	Obs	Mean	Median	Std. Dev.
WC_TA	2226	-.1388349	.0456976	.9230568	1735	.046256	.1562643	.753616
TD_TA	1958	.9742124	.0456976	.6752313	1626	.7407337	.6950999	.5299298
ROI	1929	.0309602	.0315129	.1675894	1621	.0309879	.0288525	.0994749
LOGTA	2225	6.550842	6.311999	1.747047	1735	7.650233	7.366963	1.705909
EBITDA_INT	2184	819.2037	1.871885	10189.63	1723	1219.338	1.961523	10996.46
EBITDA_TA	2220	-.0600158	.0170874	.3434455	1735	.0011951	.0249034	.1937888
CASH_TA	2208	.3514962	.2573193	.3212774	1728	.2644017	.1660679	.2748453
TURNV	2208	1.710523	1.241774	1.868889	1734	1.013466	.746144	1.128355
ROE	2214	-.0952107	.0413573	4.763281	1734	-.0278554	.018907	2.175353

Age 0= if the firm operates in the sector for less than 20 years.
Age 1= if the firm operates in the sector for more than 20 years.

Source: Own elaboration.

The Kruskal-Wallis test (Table 9) shows that the null hypothesis of equality of means in most cases should not be accepted, except for the profitability sector (ROI, ROE, EBITDAFE at 1%, EBITDA). The test applied to the two age groups shows that they are different for all the variables, except for ROI (at 5%).

Table 9. Kruskal-Wallis table.

	Solv/Insolv			**Sector**			**Age**		
Variable (avg)	Obs.	Chi-Sq.	P	Obs.	Chi-Sq.	P	Obs	Chi-Sq.	p
WC_TA	3981	382.42	0.0001**	3961	200.468	0.0001**	3961	169.476	0.0001**
TD_TA	3584	479.254	0.0001**	3584	18.885	0.0001**	3584	271.686	0.0001**
ROI	3550	427.679	0.0001**	3550	4.232	0.1205	3550	4.303	0.0380*
LOGTA	3960	309.301	0.0001**	3960	34.966	0.0001**	3960	421.537	0.0001**
EBITDA_INT	3907	531.335	0.0001**	3907	6.897	0.0318*	3907	7.356	0.0067**
EBITDA_TA	3955	573.789	0.0001**	3955	2.903	0.2343	3955	8.743	0.0031**
CASH_TA	3936	308.322	0.0001**	3936	16.882	0.0002**	3936	92.188	0.0001**
TURNV	3942	12.693	0.0004**	3942	72.104	0.0001**	3942	149.687	0.0001**
ROE	3948	279.410	0.0001**	3948	1.173	0.5562	3948	16.329	0.0001**

*: significant at 5%. **: significant at 1%.

Source: Own elaboration.

The correlation analysis (Table 10) presents high levels for most of the variables in both cases. The number of associations among ratios in the solvent group is larger than for the insolvent group. In some cases, we can observe a change in the sign (for instance, in WC_TA with CASH_TA which is positive for the solvent firms and negative for the insolvent ones) and in other cases the significance of a certain correlation (for example, LOGTA and WC_TA appear in the insolvent group, but not in the solvent firms).

Table 10. Correlation analysis according to the state [what state?]

SOLVENT GROUP									
Variable	WC_TA	TD_TA	ROI	LOGTA	EBITDA_INT	EBITDA_TA	CASH_TA	TURNV	ROE
WC_TA	1								
TD_TA	-0.1814*	1							
ROI		-0.1295*	1						
LOGTA	0.1378*	-0.2702*	-0.1755*	1					
EBITDA_INT		-0.0470*	0.1253*		1				
EBITDA_TA		-0.2867*	0.4780*		0.0919*	1			
CASH_TA	0.3040*	-0.0636*	0.2211*	-0.4117*	0.1190*		1		
TURNV	-0.0972*	0.2192*	0.1724*	-0.6267*		0.0702*	0.3443*	1	
ROE		-0.0691*	0.2029*	-0.1117*		0.1473*	0.1196*	0.0589*	1
INSOLVENT GROUP									
Variable	WC_TA	TD_TA	ROI	LOGTA	EBITDA_INT	EBITDA_TA	CASH_TA	TURNV	ROE
WC_TA	1								
TD_TA	-0.3957*	1							
ROI	0.1555*	-0.2640*	1						
LOGTA	0.1913*	-0.3195*	0.1485*	1					
EBITDA_INT			0.0609		1				
EBITDA_TA	0.4234*	-0.5545*	0.4272*	0.2972*	0.0612*	1			
CASH_TA	-0.0968*	0.0849*		-0.4104*		-0.2048*	1		
TURNV	-0.2181*	0.3182*		-0.5685*		-0.3505*	0.3580*	1	
ROE		-0.1076*	0.0913*			0.1650*			1

*: significant at 5%. **: significant at 1%.

Source: Own elaboration.

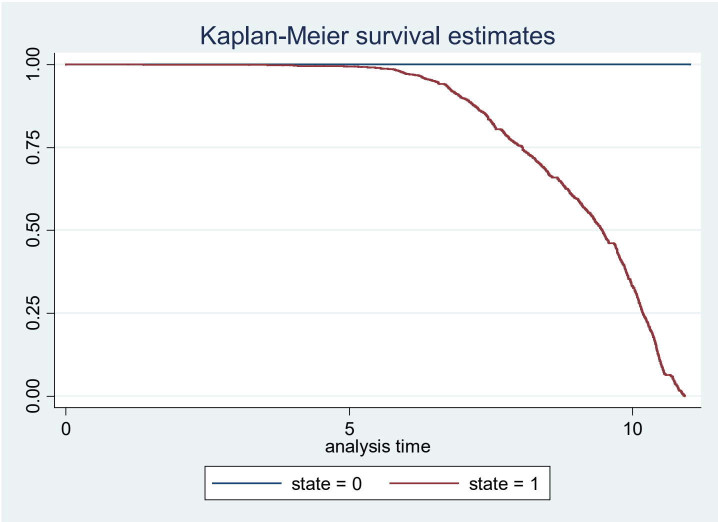
To summarize, the ratios that determine insolvency are the same when we compare the three criteria. Nevertheless, it is also true that each characteristic (number of insolvencies and age) provides fewer ratios and is not coincident with the other groups. In general, short-term solvency, return, size, indebtedness and turnover are the common features in each of the comparisons. Lastly, it is remarkable that profitability is the only factor that is the same throughout.

7. Application of survival analysis.

The time to the event was computed in months and days and we assume that the firms that appear in the database as "active" have not filed for bankruptcy. The Kaplan-Meier survival curve has been graphed by state, sector and age.

As can be seen in Figure 1, the insolvent firms exhibit a drop in the survival curve from year five while the solvent group presents a constant curve. Therefore, the probability of surviving decreases abruptly after 5 years of activity or, alternatively, most firms fail after year 5.

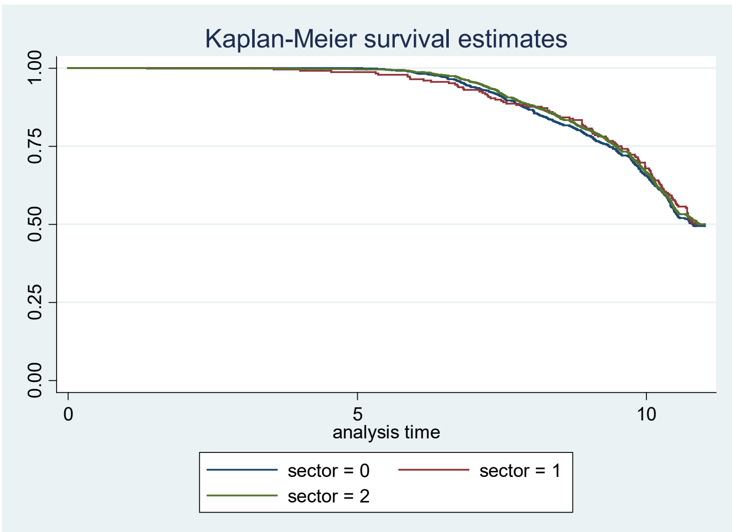
Figure 1. Kaplan Meier survival curves by state.



State =0 solvent firms
State= 1 insolvent firms.
Source: Own elaboration.

When we compare the survival curves grouping by the vulnerability of industries to insolvency (Figure 2), we find that the three curves do not show any significant differences in survival probability among the three groups. It means that the number of insolvencies has no effect on the survival probabilities of the firm or, in other words, the number of insolvencies in that industry does not affect a firm's survival.

Figure 2. Kaplan-Meier survival curves by groups.

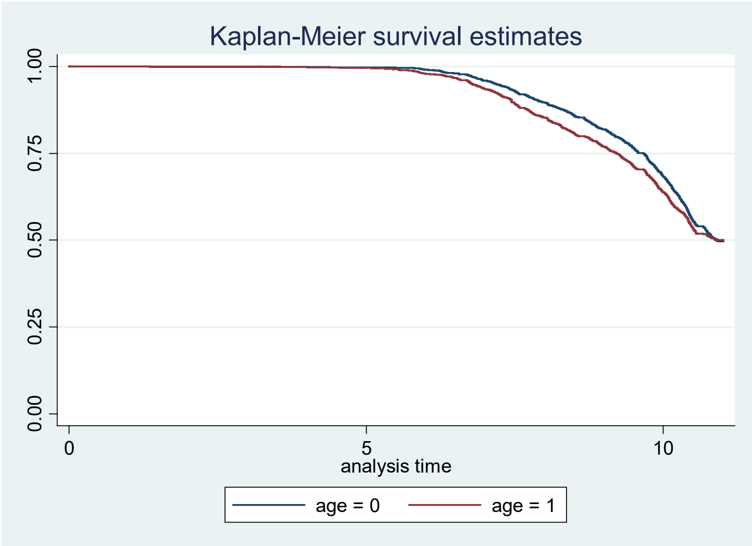


Sector =0: if the firm belongs to the sectors with the highest percentage of bankruptcies.
Sector =1: if the firm belongs to the sector with the lowest percentage of bankruptcies.
Sector =2: if the firm belongs to other sectors.

Source: Own elaboration.

Age (Figure 3) is the second grouping categorical variable and shows a difference between the two groups, even though it is not as clear at the end (past year 10). It seems that more mature firms show less probability of surviving than younger firms, but only as times advances.

Figure 3. Kaplan-Meier survival curves by groups.



Age 0= if the firm operates in the sector for less than 20 years.
Age 1= if the firm operates in the sector for more than 20 years.

Source: Own elaboration.

7.1. Estimation using models.

In the previous section, the Kaplan-Meier survival estimates allow us to conclude that no difference in survival probability exists according to sectors, although it is affected by age.

In this section, we take a deeper look at the variables that explain these results: firstly, by taking the whole sample; secondly, by the propensity to insolvency of each group; and, finally, by age. In order to do this, we have applied the Cox PH model.

The starting point is the complete set of ratios for selecting the potential candidate for the final model (p=0.05), applying the Chi-Square test for each variable. Once we had the potential covariates, we applied the test of proportionality with the significant ratios. Given that this assumption is essential for the model, the significant ratios that did not meet this requirement were incorporated as time-dependent covariates. The final step consisted of testing the possible interactions in order to improve the models.

Sectors with the highest number of insolvencies (group 0):

Table 11 shows the significant covariates (at 1%) and the interactions between variables that are significant for the hazard model.

Models 1 to 6 refer to the industries with the highest number of bankruptcies; models 7 to 12 are based on the industries with the lowest number of bankruptcies; and, finally, models 13-16 are for the reference group.

Table 11. Survival models with and without interactions for each group of sectors.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
ROI	0.2259**		0.3418*		-1.0744**								0.1709**		-1.766**
CASH_TA	0.084491**		0.0941**		-2.3625**		0.0973**						0.1149**		-2.1636**
ROE	0.97431*		0.9764*		-0.0238*										
TURNV	0.7538**		0.7633**		-0.2700**									0.9641**	-0.03652**
LOGTA		0.9633**		0.9120**		-0.0920**		0.9258**		0.8256**		-1.9158**		0.9518**	-0.0493**
EBITDA_INT							0.9999*								
WC_TA													0.8963**		-0.1093**
TD_TA													1.1290**		0.1213**
age x ROI															
1			0.0211**		-3.8579**										
age x LOGTA															
0			1.5869**		0.4618**				2.8172**		1.0357**				
1			1.6652**		0.5099**				2.9936**		1.0964**				
Age x EBITDA_INT															
0									0.9999*		-0.000156*				
1									0.9999**		-0.000128**				
Age x EBITDA_TA															
0									1.001		0.0001				
1									0.0024**		-6.0066**				
Likelihood Ratio (LR) Chi-Square		313.02**		346.73**		346.73**		114.47**		128.14**		128.14**		714.17**	714.17**
Number of Observations		1041		1041		1041		226		226		226		2096	2096

*: significant at 5%. **: significant at 1%.

Group 0: the sectors with the highest insolvency incidence.

(1) Model without interactions (hazard ratios): invariant covariates
(2) Model without interactions (hazard ratios): time dependent covariates
(3) Model with interactions (hazard ratios): invariant covariates
(4) Model with interactions (hazard ratios): time dependent covariates.
(5) Models with interactions and coefficients.
(6) Models with interactions and coefficients: time dependent covariates.

Group 1: the sectors with the lowest insolvency incidence.

(7) Model without interactions (hazard ratios): invariant covariates.
(8) Model without interactions (hazard ratios): time-dependent covariates.
(9) Model with interactions (hazard ratios): invariant covariates.
(10) Model with interactions (hazard ratios): time-dependent covariates.
(11) Model with interactions and coefficients.
(12) Model with interactions and coefficients: time-dependent covariates.

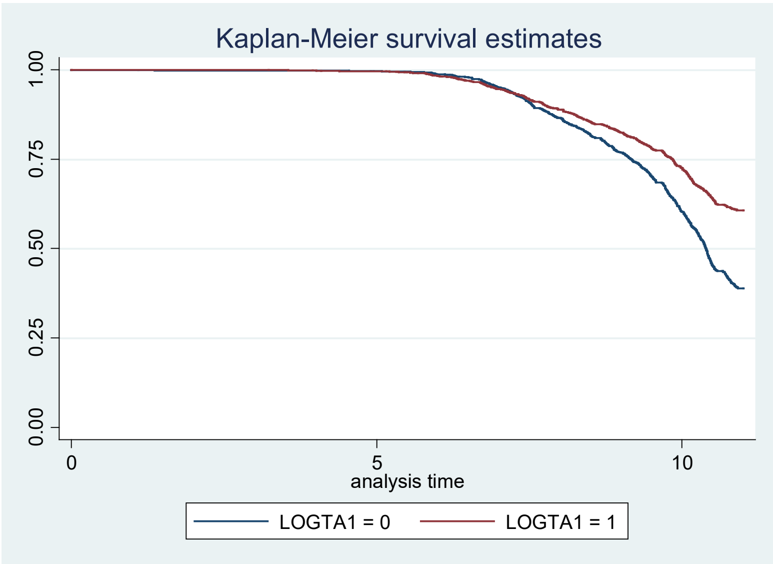
Group 2: reference group.

(13) Model without interactions: invariant covariates.
(14) Model without interactions: time-dependent covariates.
(15) Model with interactions and coefficients.
(16) Model with interactions and coefficients: time-dependent covariates.

Source: Own elaboration.

Regarding the first group (column 1), all the ratios have a negative effect on the time of insolvency, especially cash to total asset (0.084491) and ROI (0.2259), which show the strongest impact on the hazard functions while asset turnover (0.7538) and ROE (0.97431) have only a slight effect. Therefore, liquidity and asset return are the two significant covariates for determining the time to survive (column 2). LOGTA has been selected and included in the model as a time-dependent variable. In order to make this interpretation, the variable has been divided into two discrete groups: below and above the median. For group 0 (below the median) the curve is above group 1 (above the median) until year 7-8. Subsequently, the first group presents a decline of the survival curve (Figure 4).

Figure 4. Kaplan-Meier survival curves for LOGTA.



LOGTA1=0 if the firm is below the median
LOGTA1=1 if the fim is above the median.
Source: Own elaboration.

The model (columns 3 and 4) with interactions includes some significant relationships. The years of activity (age) and ROI allow us to conclude that in the firms that are less than 20 years old the effect of an increase of profitability is less than for the firms in the second group (*age 0 x ROI* : exp (-1.0744) = 0.3415 (decrease by 64%); *age 1 x ROI*: exp (-1.0744 -3.8579) = 0.007 (decrease by 99%); *age 0 x LOGTA* : exp (0.4618) = 1.5869 (increase by 58%); *age 1 x LOGTA*: exp (0.5099523) = 1.6651 (increase by 66%)). Therefore, an increase in profitability is more important for older firms than for younger firms. The second interaction age x LOGTA shows the effect of an increase in size depending on age. This result is inconsistent as in each case it is greater than one and means that an increase in size also boosts insolvency. Given that LOGTA is a time dependent covariate, it implies that the interaction with this variable does not fulfil the proportionality assumption.

The last columns (5 and 6) present the model with interactions and, instead of the hazard ratio for each variable, the coefficient for each variable appears.

Sectors with the lowest number of insolvencies (group 1):

The hazard models here are different from the previous one (columns 7 to 12). If we look at the model without interactions (7-8), the only variables in common with group 0 are CASH_TA and LOGTA. Therefore, it means that liquidity and size are the characteristics that determine the survival time. Neither profitability nor indebtedness play a role in this group. The second observation is the effect on the time of insolvency and here, surprisingly, only cash is really important as a one unit increase in cash decreases the rate of insolvency versus solvency by 99% (hazard rate: 0.0973). The ratio EBITDA_INT has a marginal effect, only a reduction of 1% of the rate of insolvency versus solvency (hazard rate: 0.9999). The role of size is similar to the previous group.

The next question is the inclusion of interactions (9 to 12). Here, again, some unexpected results emerge. The single ratios cease to be significant (except LOGTA) and the interactions with age are the only covariates, in particular, age x LOGTA (not consistent, as it was mentioned earlier), age x EBITDA_INT and age x EBITDA_TA. This interpretation (*age0 x LOGTA* increases the rate of insolvency by 181%; *age1 x LOGTA* increases the rate of insolvency by 199%; *age0 x EBITDA_INT* decreases the rate of insolvency by 1%; *age1 x EBITDA_INT* decreases the rate of insolvency by 1%; *age0 x EBITDA_TA* increases the rate of insolvency by 1%; *age1 x EBITDA_TA* decreases the rate of insolvency by 99%) is misleading for age x LOGTA, which is the only interaction with a meaningful effect. The interaction of age x EBITDA_INT is not significant and age x EBITDA_TA has a significant effect only for group 1. Therefore, we can conclude that in this case, although the model is significant, the meanings of the interactions are confusing.

Reference sectors (group 2):

This includes firms that do not belong to the other sectors in order to make comparisons. Given that this is the most heterogeneous, the results per se could be less meaningful than the others (columns 13-16).

This group is more similar to the one of the highest percentage of insolvencies) than the other. Effectively, ROI (0.1709), CASH_TA (0.1149), LOG_TA (0.9518) and TUNV (0.9641) are significant in both groups 0 and 2. Nevertheless, ROE appears in the first group, but not here, and WC_TA and TD_TA appear here, but not in the 0 group. The similarities with group 1 are very small as the only variables that appear in both models are CASH_TA and LOGTA.

The interpretation of the signs allows us to say that an increase of one unit in WC_TA (0.8963) reduces the hazard of being insolvent by 11%; ROI is more effective (0.1709), with a reduction of 83%, and the same happens with CASH_TA (0.1149), with a reduction of 89%. Although the same interactions with age were applied in this sector, none of them was significant.

The group most affected by insolvency and the reference group shows some common factors, such as return and turnover. The group least affected by bankruptcy is the most dissimilar as the only significant variables are based on EBITDA.

The main results allow us to confirm that both liquidity and size are the main factors in determining survival time in any of the analyzed groups. Profitability and turnover are important for determining the survival of a firm in the reference group and the one with the highest number of insolvencies. This is not the case for the second group. This one is the most dissimilar, not only because of the explanatory variables, but also due to the interaction signs. We can therefore conclude that the characteristics of this group are distinct from the others.

8. Logit results.

We applied logit analysis with the objective of estimating the probability of insolvency for each group. The results are shown in Table 12.

The comparison of the models with and without interactions reveals some interesting insights. The group with the highest numbers of insolvencies shows that an increase by one unit in return (ROI, 0.0059326), liquidity (CASH_TA, 0.0351236), turnover (TURNV, 0.7779144), and size (LOGTA, 0.5797339) decreases the odds of insolvency (vs. solvency), but an increase in one unit by short-term solvency (WC_TA, 1.926575) and age (1.5935) increases the same probability. The model with interactions shows that age is an important variable in this group; it appears as a single variable and in conjunction with indebtedness (TD_TA 1.41638 for value 0 and 4.029322 for value 1) and return (ROI, 0.0002531).

Table 12. Logit models for each group.

	Group 0		***Group 1***		***Group 2***	
Odd ratios	Model without interactions	Model with Interactions	Model without interactions	Model with interactions	Model without interactions	Model with interactions
WC_TA	1.926575**		.0990294*		.6513558**	.4933654**
TD_TA			16.57591**		2.580793**	2.586244**
ROI	.0059326**	.0291733**			.0366056**	.0675444**
CASH_TA	.0351236**	.0510667**			.0587385**	.0612975**
ROE					.9553534**	.9550634**
TURNV	.6679144**	.6616689**		.373514**		.4679028**
LOGTA	.5797339**	.5733134**	.2315606**	.2288935**	.4231289**	.4212577**
EBITDA_FE			.9998674			
EBITDA_TA			373.3959			
Age (1)	1.5935**		2.943365		1.839153**	1.972945**
Interactions						
age x TD_TA						
0		1.41638*				
1		4.029322**				
age x ROI						
1		.0002531**				.0990508 *
age x WC_TA						
0				.5014957		
1				.0003673**		1.559086*
age x LOGTA						
1				1.2407		
Constant	112.0871**	137.3461	15608.28**	98656.82**	848.8225**	859.8955**
Pseudo R^2	0.2273**	0.2453**	0.4716**	0.4445**	0.2841**	0.2872**
Number of observations	945	945	225	225	2096	2096

*: significant at 5%. **: significant at 1%.

Source: Own elaboration.

The firms that belong to the sectors with the lowest number of insolvencies show that short-term solvency (WC_TA, 0.0990294) and size (LOGTA, 0.2315606) show a fall in the relative probability of insolvency versus solvency. Nevertheless, indebtedness (TD_TA, 16.57591) has the opposite effect. The inclusion of the interactions almost makes the previous single ratios disappear and the only relevant factors with a negative effect on the odds of insolvency are turnover (TURNV, 0.373514) and size (LOGTA, 0.2288935). The significant interactions are age x WC_TA, which decreases the odds by 0.5014957 in the value 0 and 0.0003673 in the value 1, so the effect is stronger for the first age group. The second interaction is not significant.

The reference group (2) shows a similar pattern to the first group. Regarding the first model without interactions, the variables with a negative effect of insolvency are short-term solvency (WC_TA, .6513558), return (ROI, 0.0366056 and ROE, 0.955534), liquidity (CASH_TA, .0587385), and size (LOGTA, 0.4231289). The variables with the opposite effect are indebtedness (TD_TA, 2.580793) and age (1.839153). The model with interactions is very similar, except for turnover, which now appears with a negative effect (TURNV, 0.4679028), and the significant interactions are age x ROI (0.0990508 at 5%) and age x WC_TA (only significant for Group 1 (1.559086 at 5%).

The group with the highest numbers of insolvency and the reference group are very similar with respect to the explanatory variables and the fit of the model. The most dissimilar is group 1 (with the lowest number of insolvencies) not only because of the number of single ratios and the composition, but also because of the fit of the model. Therefore, we can conclude that this group responds to different factors in order to explain the time and the probability of bankruptcy.

The comparison of survival models with logit models allows us to detect some differences, bearing in mind that each technique pursues different objectives.

Group with the highest number of insolvencies: if we look at the different selected variables in the models, the survival model without interactions selects ROE as significant (negative effect), but in the logit it does not appear and instead, WC_TA (positive) and age (positive) appear. The addition of interactions produces more differences. For instance, the survival model includes age x LOGTA (inconsistent), but it is not present in the logit model. The logit, nevertheless, selects as a meaningful variable age x TD_TA that the survival model does not select. Therefore, we can conclude that ROE is significant when we want to estimate the survival time of the firm in this group, but when we need to study the odds of insolvency WC_TA appears instead. The interactions clearly show that age is significant and it can be said that the effect is less positive in the group of older firms than in the younger group.

Group with the lowest number of insolvencies: the unique ratio that appears in both techniques is LOGTA. CASH_TA is only relevant for the survival model and WC_TA and TD_TA only appears in the logit. When the interactions are included in this group the only common variable is LOGTA, TURNV is shown in the logit and the interactions with age are different, except for age x LOGTA which is not significant in the logit (in the survival model age x EBITDA_INT and age x EBITDATA, in the logit age x WC_TA). Here, we can state that while liquidity (CASH_TA), interest coverage (EBITDA_INT) and size (LOG_TA) are the only relevant factors in order to determine the time of survival, the odds of insolvency versus solvency are moulded by short-term solvency, indebtedness, and size.

Reference group: the differences in the model without interactions come from ROE and AGE that appear in logit, but not in the survival model. It is worth mentioning that ROE has a negative effect on the odds, but age shows a positive sign. The survival model only selects variables, not interactions. From these results, we can state that the factors that determine the survival time and the odds of insolvency are more similar here than in the other groups. Short-term solvency (WC_TA), asset return (ROI), liquidity (CASH_TA), and size (LOGTA) are the common factors in both techniques. Age only appears in the logit model with a positive sign, so implying that the change from the younger to the older group increases the odds of insolvency.

To summarize, if liquidity and size are the factors that determine the time to insolvency, the occurrence of bankruptcy is explained by short-term solvency, size, and turnover. This means that the event depends on more variables than the time to the event (Table 13).

Table 13. Main findings of hazard models and logit models.

GROUP	HAZARD MODELS	LOGIT MODELS
The highest insolvency	▪ Cash and profitability show negative effects on insolvency ▪ No selected ratio presents a positive sign. ▪ The interaction of age and profitability shows that it is more powerful for the older than the younger firms.	▪ Return, liquidity, turnover and size decrease insolvency odds. ▪ Short-term solvency and age increase insolvency probability.
The lowest insolvency	▪ Liquidity and size are the determinants of survival. ▪ Neither profitability nor indebtedness play a role. ▪ Misleading interactions	▪ Short-term solvency and size decrease probability of insolvency. ▪ Indebtedness has the opposite effect.
The reference group	▪ Profitability, cash, size and turnover are significant.	▪ Short-term solvency, return, liquidity and size have a negative effect on insolvency. ▪ Indebtedness and age have the opposite effects.

Source: Own elaboration.

9. Discussion.

The most remarkable results to emerge from the data are that the survival for insolvent firms drops from the five year mark onwards; the propensity to insolvency in the industry does not play a role; and the years of activity seem to be important as the more years there are, the lower is the probability of survival. Regarding the variables to explain survival, liquidity and size appear for all the industries, but profitability and turnover are also important for the sectors with the highest level of bankruptcies.

The probability of insolvency estimated by logit shows differences among groups and the variables that explain it are more similar when the groups have a large number of insolvencies. In general, the variables coincide with the previous ones.

As far as we know, this is the first time that a study analyses the influence of industry vulnerability to default directly in the sample and applies two different techniques. The results widen our knowledge of the effect of industry on survival and the probability of insolvency.

The results confirm some of those found in the previous literature. For example, the lack of differences among groups in the survival models is in line with Kenedy (2000). However, it does not support the importance of including industry effects in hazard models (Chava & Jarrow, 2014; Lang & Stulz, 1992). The effect of age is difficult to compare, as it has been included as a categorical variable here. Nevertheless, it is in agreement with Berkovitch and Israel (1998), who also found that failure is higher for mature firms.

With respect to the relevance of liquidity, size, profitability and turnover as significant in the survival and the logit, previous literature supports these findings: for instance, profitability (Chava &

Jarrow, 2004, among others) and size (Huang & Lee, 2013, James & Kazalislan, 2014, among others), although our study differs from most of the previous research as this last variable has been computed using turnover, but not assets.

It is worthwhile noting that liquidity confirms the finding of James and Kazalislan (2014) about the use of more cash in industry with significant risk exposure. In our case, the relevance of cash to total asset can be seen in the group of the highest level of insolvencies.

It is plausible that a number of limitations may could have influenced the results obtained. Firstly, in the sample selection as we used only SME entities; secondly, the period analyzed (2012-2016), in which the Spanish economy moved from depression to a certain stabilization; and finally, the variables. The use of the percentage of insolvencies over the population to define the vulnerability of an industry could be a reasonable measure, but other measures should be considered, especially the concentration index (Chiu, Pena & Wang, 2013; Zhang, Altman & Yen, 2010).

Further work needs to be done to analyze in greater depth the fact that survival of the firm is not affected by the vulnerability of the industry and the fact that the years of activity have a negative effect on survival.

10. Conclusions.

The usefulness of comparing sectors with the highest and lowest number of insolvencies is that it highlights the similarities and differences both in the process to bankruptcy and in the occurrence of the event. Besides, the analysis has been extended to see if the years of activity plays a role in insolvency.

The main conclusion is that sector does not seem significant in determining the length of time to bankruptcy (or survival), but it seems to be more important in the probability of the event. However, the analysis of the causes that lead to the insolvency allow us to conclude that some of them are common to all the groups (liquidity and size have a positive effect on time of survival), but others are particular for each group (especially for the one with the lowest number of insolvencies). When we compare it with a reference group made up of a large variety of sectors, the group that exhibits the higher number of bankruptcies is similar and the variables that determine insolvency are common among them.

The probability of insolvency is determined by some variables that also appear in the survival models and, in this case, the ratios show more similarities among groups than in the previous models. The occurrence of the event is mainly explained by turnover and short-term solvency. Size and turnover have negative effects on bankruptcy. Age is also a common factor, but with a positive effect.

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