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Survival analysis for predicting bankruptcy in small and medium-sized enterprises (SMEs): A case study approach

Análisis de supervivencia sobre la predicción de la quiebra en pequeñas y medianas empresas (PYMEs): Un enfoque de estudio de caso

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Abstract
This study investigates the determinants of small and medium-sized enterprise (SME) survival through a quantitative analysis of financial and managerial factors. Using a dataset of SMEs observed over a ten-year period, the research applies survival analysis techniques based on the nonparametric Kaplan–Meier estimator and complementary log–log regression to identify predictors of business insolvency. The results show that firm survival is positively influenced by financial structure, return on assets, EBITDA, and human capital productivity, whereas excessive working capital is negatively associated with longevity. By incorporating underexplored variables such as financial results and employee productivity, this study broadens the empirical scope of survival analysis beyond traditional financial ratios. The findings contribute to the strategic management literature by identifying measurable financial and operational indicators that can serve as early warning signals of business failure. Although the data are drawn from a regional sample, the managerial implications are broadly applicable to SMEs operating across diverse economic and institutional contexts.

Keywords: SME survival; insolvency prediction; bankruptcy prevention; financial management; strategic business analysis
JEL Classification: C41; G33; L26; M10

Resumen
Este estudio investiga los factores determinantes de la supervivencia de las pequeñas y medianas empresas (pymes) mediante un análisis cuantitativo de factores financieros y de gestión. Utilizando un conjunto de datos de pymes observadas durante un período de diez años, la investigación aplica técnicas de análisis de supervivencia basadas en el estimador no paramétrico de Kaplan-Meier y la regresión logarítmica complementaria para identificar los predictores de la insolvencia empresarial. Los resultados muestran que la supervivencia de las empresas se ve influida positivamente por la estructura financiera, el rendimiento de los activos, el EBITDA y la productividad del capital humano, mientras que un exceso de capital circulante se asocia negativamente con la longevidad. Al incorporar variables poco exploradas, como los resultados financieros y la productividad de los empleados, este estudio amplía el alcance empírico del análisis de supervivencia más allá de los indicadores financieros tradicionales. Los resultados contribuyen a la literatura sobre gestión estratégica al identificar factores financieros y operativos medibles que pueden servir como señales de alerta temprana de la quiebra empresarial. Aunque los datos se han extraído de una muestra regional, las implicaciones para la gestión son ampliamente aplicables a las pymes que operan en diversos contextos económicos e institucionales.

Palabras clave: supervivencia de pymes; predicción insolvencia; prevención quiebra; gestión financiera; análisis estrategia negocio
Clasificación JEL: C41; G33; L26; M10

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1. Introduction

The analysis of small and medium-sized enterprise (SME) survival has become increasingly relevant given its implications for employment, innovation, and sustainable economic growth worldwide. Predicting business insolvency remains a central issue in management and finance research because the early identification of risk factors enables managers to make timely strategic decisions to avoid bankruptcy and preserve economic stability (Branch, 2002; Wu, 2010). Over recent decades, survival analysis has consolidated as a robust methodological framework for studying firm longevity, combining statistical sophistication with managerial applicability.

Numerous studies have examined the determinants of business failure in different economies, including Spain, providing valuable empirical evidence that aligns with broader international findings. Most of this literature has focused on financial ratios as predictors of insolvency (Altman, 1968; Beaver, 1966; Ohlson, 1980; Serer et al., 2009). Other analyses have extended the scope of investigation to external and contextual dimensions—such as urbanization, gender, and managerial education (Bellido-Jiménez et al., 2021)—and to sector-specific contexts such as the hospitality industry, where survival models have proven effective (Gemar et al., 2019).

From a broader economic perspective, Spain offers an interesting empirical context for studying business dynamics and survival, as it exhibits entrepreneurial patterns and growth trends comparable to those of other European economies. Regional data, for instance, reveal strong entrepreneurial intent (Ventura Fernández & Martínez Martínez, 2022) and sustained firm creation rates over the past decade (INE, 2023). Such evidence underscores the importance of studying SME survival not only at the local level but also as part of a global conversation on business resilience and competitiveness.

The empirical literature also highlights internal determinants of survival, including equity capital, return on assets, financial structure, and firm size (Bruderl & Schussler, 1990; Castaldo et al., 2023; Kaniovski et al., 2008; Li & Hamblin, 2003). However, less attention has been paid to the operational and managerial dimensions of business continuity—particularly variables such as financial results (e.g., extraordinary income or losses) and employee cost productivity, which are key indicators of managerial efficiency and strategic decision-making (Jackson et al., 2013; Verwijmeren & Derwall, 2010). In this regard, previous research has suggested that incorporating nonfinancial variables enhances the explanatory power of survival models (Nießner et al., 2022) and improves their predictive accuracy for the early detection of corporate distress (Kim, 2011; Misas, 2008).

Although much of the available evidence originates from national or sectoral contexts—such as studies conducted among Spanish SMEs (Buil Fabregá & Rocafort Nicolau, 2016) or in specific industries (Gemar et al., 2019)—the methodological framework and determinants examined in this research are generalizable to SMEs operating across diverse institutional and economic environments. By adopting an integrated financial–managerial perspective, this study applies survival analysis techniques, specifically the nonparametric Kaplan–Meier estimator and complementary log–log regression, to identify the structural factors that influence SME survival over a ten-year period.

The contribution of this paper is twofold. First, it broadens the scope of empirical survival analysis by incorporating underexplored variables that link financial performance to strategic and operational management. Second, it offers practical insights for business decision-makers by identifying measurable financial and managerial indicators that can serve as early warning systems to anticipate insolvency and enhance organizational resilience.

The remainder of the paper is organized as follows: Section 2 reviews the literature and develops the research hypotheses. Section 3 describes the materials, data, and methods used in the empirical analysis. Section 4 presents the main results, and Section 5 discusses these findings in relation to existing research. Finally, Section 6 concludes the paper by outlining the theoretical and practical implications, as well as the study's limitations and avenues for future research.

2. Literature review and hypothesis development

2.1 Theoretical models of bankruptcy

Early research on business failure traces back to Marshall (1980) and Schumpeter (1934). Their ideas were later applied to the study of industrial organization by scholars such as Gibrat (1931) and Bain (1956). The initial focus of the literature was on developing theoretical models capable of explaining the process of corporate bankruptcy, such as the single-period model (Scott, 1981) and the gambler's ruin model (Wilcox, 1973).

Single-period models assume that firms exist for only two accounting periods—created in the first and liquidated in the second. A firm is considered bankrupt if its liquidation value falls below the amount owed to creditors (Scott, 1981). Although this represents the simplest form of bankruptcy modeling, its predictions diverge considerably from empirical evidence, as single-period models account only for equity and exclude cash flows (Black & Scholes, 1973; Merton, 1974; Schwartz, 1977).

The gambler's ruin model, by contrast, assumes that changes in a firm's capital result from operating cash flows. A firm fails when its working capital becomes negative. This model further assumes that firms are isolated from financial markets and must finance losses by selling assets (Wilcox, 1973). Despite its simplicity, the gambler's ruin model represents an important step forward by incorporating book values instead of liquidation values, thereby improving the empirical applicability of bankruptcy models (Borch, 1967; Santomero & Vinso, 1977; Tinsley, 1970).

Both approaches assume that companies can access external capital to cover losses by issuing debt or equity, thus remaining in business indefinitely. Under this assumption, firms remain solvent as long as their market value is positive, even if operating results are ignored (Scott, 1976, 1981). To address these limitations, empirical methods have since been developed to more accurately discriminate between firms that fail and those that remain solvent, making bankruptcy modeling increasingly consistent with real-world data.

2.2 Empirical models of business failure

According to Kliestik et al. (2017), academic research on business survival began in the 1930s with Paul Joseph FitzPatrick, who conducted a comparative analysis of financial ratios between solvent and failing companies (FitzPatrick, 1932). The earliest predictive models of corporate bankruptcy employed univariate regression analysis (Beaver, 1966). Although these methods were useful as an initial approximation, they proved insufficient, as multiple factors influence business failure. This limitation led to the development of a wide range of multivariate techniques.

These early analyses provided the foundation for later survival models. One of the most influential was Altman's (1968) model, which identified a linear combination of variables to discriminate between failing and surviving firms. The model gained broad acceptance among financial institutions during the 1980s. Other statistical regression approaches followed, such as Ohlson's (1980) logistic regression model. Overall, the most widely used statistical techniques for predicting business failure include multiple discriminant analysis, logistic regression, and survival analysis.

A variety of factors have been explored in relation to the probability of business survival. The most commonly examined internal variables include firm size, financial structure, performance, and liquidity metrics (Ohlson, 1980). Human capital–related aspects have also received attention (Amankwah-Amoah, 2015). Regarding external factors, researchers have studied the effects of crisis contexts (Udenio et al., 2015), market conditions (Chiu et al., 2013), and business networks (Tobback et al., 2017).

Early literature also focused on the entry of new firms into markets, framing entry and exit as normal and simultaneous processes within the economic cycle (Evans & Siegfried, 1992; Love, 1996). Firm size—often measured by investment in assets—can delay market exit but may also increase insolvency risk (Renski, 2011). Although the relationship between firm age, size, and survival has been well established, empirical validation has largely been confined to the manufacturing sector (Dunne & Hughes, 1994; Geroski, 1995; Sutton, 1997).

Some studies suggest that failure can occur not only among firms facing financial distress but also among profitable companies (Wennberg et al., 2010). While profitability is generally assumed to promote growth and reduce insolvency risk, rapid expansion may, under certain conditions, undermine survival prospects (Delmar et al., 2013).

2.3 Factors affecting business survival

The above literature review identifies several factors relevant to the survival or failure of firms. Based on prior empirical research, a set of variables has been selected that may influence business continuity and can be managed strategically to mitigate insolvency risk.

2.3.1 Equity capital

Equity represents the portion of capital owned by the company. Business mortality linked to initial resources tends to peak between one and fifteen years after a firm's creation (Bruderl & Schussler, 1990). Research conducted in Barcelona shows that, at the onset of the financial crisis, firms that survived typically relied on equity as a key source of financing, which reduced indebtedness and strengthened their likelihood of survival (Buil Fabregá & Rocafort Nicolau, 2016).

In the Italian market, access to bank credit has also been shown to improve the resilience of start-ups (Castaldo et al., 2023). However, among more established firms, the relationship between bank credit and business survival appears negative, whereas non-bank credit correlates positively with longevity (Åstebro & Bernhardt, 2003). Although much of the literature emphasizes the role of bank resources in survival, comparatively less attention has been paid to the contribution of equity financing.

H1. *Equity capital has a positive effect on the survival of SMEs*.

2.3.2 Return on assets (ROA)

Return on assets (ROA) is a widely used indicator of firm performance and has proven to be highly predictive of corporate investment outcomes (Kusuma, 2021). It also enables efficient forecasting of company turnover (Ichsani & Suhardi, 2015).

Studies of Spanish firms in the pre-bankruptcy phase have found that ROA significantly influences business failure and constitutes a key determinant of corporate survival (Segovia-Vargas & Camacho-Miñano, 2012). Because ROA provides a reliable measure for predicting cash flows, it serves as an essential indicator for assessing the long-term viability of companies.

H2. *Return on assets has a positive effect on the survival of SMEs*.

2.3.3 Gross operating result (EBITDA)

Gross operating result—often measured as earnings before interest, taxes, depreciation, and amortization (EBITDA)—is a central indicator of a firm's financial health. However, its predictive value in bankruptcy detection models has been questioned, as these results can be legally adjusted by financial managers to produce desired outcomes (Kovacova et al., 2021). Nevertheless, studies employing logistic regression models have found that EBITDA- and cash-flow–based coverage ratios correctly predict bankruptcy in approximately 66% to 76% of cases (Jacek, 2017).

In Spain, a survival analysis of firms founded in Barcelona during the financial crisis revealed that surviving companies commonly exhibited positive EBITDA values (Buil Fabregá & Rocafort Nicolau, 2016). Although EBITDA may be subject to managerial manipulation for commercial or fiscal reasons, prior research supports its relevance as an indicator of firm sustainability, warranting further empirical testing.

H3. *Gross operating result (EBITDA) has a positive effect on the survival of SMEs*.

2.3.4 Financial structure

Traditionally, survival analysis has emphasized financial attributes as key determinants of business continuity (Kim, 2011). These indicators have a long history in the literature as predictors of firm survival, with numerous studies showing that a sound financial structure—measured through ratios derived from company financial statements—has a positive effect on longevity (Altman, 1968; Beaver, 1966; FitzPatrick, 1932).

Empirical research on the financial distress of Chinese companies demonstrates that financial restructuring significantly affects bankruptcy risk (Zhou et al., 2022). In Spain, a study using logit regression found that the level of indebtedness is a strong predictor of business insolvency (Mures Quitana & García Gallego, 2004). Accordingly, the health of the financial structure in this study will be assessed through indebtedness and solvency ratios.

H4. *SME survival is positively associated with a stronger financial structure*.

2.3.5 Size

Firm size is among the most frequently analyzed variables in survival research, as it is easy to measure using various indicators. Many studies have found a positive relationship between firm size and survival (Kaniovski et al., 2008; Mas-Verdú et al., 2015). However, other studies—such as those focusing on UK manufacturing firms—have not validated size as a significant factor (Li & Hamblin, 2003). In some cases, rapid expansion can even increase bankruptcy risk (Gu & Gao, 2000).

This study measures firm size through fixed assets. Although fixed assets have rarely been examined independently as a determinant of survival—often appearing instead as part of ratio-based analyses—they remain a relevant proxy for firm size (Arquero Montaño et al., 2009; Masa Lorenzo et al., 2017).

H5. *Firm size has a positive effect on the survival of SMEs*.

2.3.6 External financial costs and revenues

The cost and return on external financing reflect the firm's balance of resource use in capital markets. Some theories suggest offsetting debt costs with capital-market returns, though evidence shows that managers are often reluctant to divest assets and expose their capital to risk (Jackson et al., 2013; Magni, 2015). However, when the level of debt increases, investors' risk preferences tend to rise correspondingly (Kanatas & Qi, 2005).

Survival models have proven useful in predicting financial risk and insolvency within supply chains, though they are less effective in estimating timing (Dellana & West, 2016). In Slovenia, debt-to-equity conversion during corporate restructuring was found to be strongly and negatively associated with bankruptcy risk (Cepec & Grajzl, 2020). In Spain, the cost of borrowing has shown an inverse relationship with firm survival (Misas, 2008). The present study analyzes external financial costs and revenues through the *financial result* variable, an aspect still underexplored in survival research.

H6.*The balance of external financial costs and revenues has a positive effect on the survival of SMEs.*

2.3.7 Human capital cost structure

The composition of the human capital cost structure is closely linked to business survival, as high personnel costs can reduce earnings, increase turnover, and hinder talent retention (Graham et al., 2013; Verwijmeren & Derwall, 2010). Research on Spanish firms has found that personnel cost ratios are reliable indicators for anticipating business failure (Ferrando Bolado & Blanco Ramos, 1998; Laffarga & Pina, 1995).

While extensive literature addresses employee welfare as a determinant of survival, relatively little attention has been paid to staff productivity as a potential risk factor for bankruptcy (Verwijmeren & Derwall, 2010). To evaluate human capital structure, this study analyzes the ratio of personnel costs to revenues, which serves as a measure of workforce productivity.

H7.*SME survival is positively associated with higher human capital productivity.*

2.3.8 Working capital

Firms require adequate working capital to meet day-to-day financial obligations, and effective working-capital management is essential for both survival and growth (Nwankwo & Osho, 2010). Studies of Qatari firms show that shorter cash conversion cycles, reduced collection periods, and longer payment periods are linked to greater profitability (Aldubhani et al., 2022). Similar results have been reported in African markets (Kabir et al., 2021).

In Spain, insufficient working capital has been associated with future financial distress, thereby threatening firm survival (Ferrando Bolado & Blanco Ramos, 1998). Although positive working capital generally reflects a sound financial position, negative working capital is not necessarily a sign of potential bankruptcy; under certain conditions, it can yield higher returns on capital. It is therefore essential to account for industry-specific operational dynamics (Panigrahi, 2015). The differing results across regions and industries underscore the importance of examining working capital as a determinant of SME survival.

H8.*Working capital has a positive effect on the survival of SMEs.*

3. Materials and methods

Survival is defined as the time elapsed until a specific event of interest occurs (Cox & Oakes, 2018). The objective of this study is to analyze the evolution of time to failure and survival probabilities over a given period (Allison, 1984). Survival models are particularly suitable in this context because the distribution of errors in business insolvency data is typically skewed to the right (Hosmer et al., 2008).

Survival analysis uses a binary variable to indicate whether the event of interest occurs. Observations begin with a value of zero, meaning the event has not yet occurred, and continue until the event takes place or the observation period ends. The start and end dates may differ for each firm, as enterprises enter and exit the dataset at different times during the observation period. When the event does not occur within the study period, the observation is referred to as *censored* or *incomplete*; when it does occur, it is considered *uncensored* (Jenkins, 2005). It is also necessary to include a variable measuring firm duration in the sample, which represents the time until the event of interest occurs (Esteve-Pérez et al., 2008).

Several techniques are available for estimating survival times, both parametric and nonparametric. Because parametric models impose specific assumptions on the hazard function (Kalbfleisch & Prentice, 2002), they were excluded from this analysis. Instead, the nonparametric Kaplan–Meier estimator is employed, as it has the advantage of not requiring restrictive assumptions about the underlying model.

The empirical analysis is conducted in four stages. First, a descriptive analysis of the variables is performed (Baltagi, 2021). Second, a nonparametric test for differences in medians is applied using the Mann–Whitney *Z* statistic. Third, a survival analysis is carried out with the nonparametric Kaplan–Meier estimator, followed by a smoothed hazard ratio estimation. Finally, a complementary log–log logistic regression is estimated. Logarithmic transformations are incorporated into the model to stabilize the regressors, reduce the influence of outliers, and eliminate the effects of measurement units on the variables.

3.1 Kaplan–Meier estimator

The Kaplan–Meier estimator is one of the most widely used survival analysis techniques because it is nonparametric and imposes very few restrictions. Its only assumption is that censored observations continue to behave similarly to uncensored ones until the event of interest occurs. This condition, known as *noninformative* or *random censoring*, applies when each observation has a censoring time that is independent of the event being studied. The observed survival time is therefore the minimum between the censoring time and the event (Efron, 1988).

To implement the model, all survival times are arranged from the shortest to the longest, with the goal of determining the number of exits and censored observations over time. For each period, the survival function provides an estimate of the individual probability of survival (Jenkins, 2005). It is assumed that the time axis can be divided into a sequence of contiguous, nonoverlapping intervals whose limits are $a_0 = 0$, a_1, a_2, a_3, ..., a_k. These intervals are represented as follows:

$$[0 = a_0, a_1]\,, (a_1, a_2)\,, (a_2, a_3) \cdots, (a_{k-1}, a_k = \infty) \;\; (1)$$

Time was discretized into yearly intervals, with calculations for year *j* based on (a_{j-1}, a_j). Survival analysis seeks to obtain a time-dependent function whose value represents the probability that the event of interest will occur. This failure function, *F(t)*, before the start of year *j*, is expressed as:

$$F(t) = P_{\Gamma}(T \leqslant a_{j-1}) \;\; (2)$$

The survival function, derived from the hazard function, gives the probability that a failure will *not* occur. The probability of survival up to time *t* is therefore:

$$P_{\Gamma}(T > a_{j-1}) = 1 - F(a_{j-1}) = S(a_{j-1}) \;\; (3)$$

The survival function at the end of year *j* is:

$$P_{\Gamma}(T > a_{j-1}) = 1 - \overline{F}(a_j) = S(a_j) \;\; (4)$$

Finally, the probability of exiting the market within a given interval is calculated as:

$$P_{\Gamma}(a_{j-1} < T < a_j) = F(a_j) - F(a_{j-1}) = S(a_{j-1}) - S(a_j) \;\; (5)$$

3.2 Complementary Log–Log logistic regression

The complementary log–log (cloglog) model estimates the parameters that describe risk over a continuous period, taking into account the discrete-time nature of the survival data (Jenkins, 2005). The discrete-time interval hazard function, $h(a_j,X)$—also written as $h_j(X)$—is defined as:

$$h_j(X) = \frac{S(a_{j-1}, X) - S(a_j, X)}{(a_{j-1}, X)} = 1 - \frac{S(a_j, X)}{(a_{j-1}, X)} = 1 - \exp[\lambda(H_{j-1} - H_j)] \;\; (6)$$

This expression can be transformed into:

$$\log(-\log[1 - h_j(X)]) = \beta' X + \gamma_j \;\; (7)$$

or equivalently:

$$h(a_j, X) = 1 - \exp[-\exp(\beta' X + \gamma_j)] \;\; (8)$$

Here, γ_j represents the logarithm of the difference between the integrated baseline hazard *θ(t)* evaluated at the beginning and end of the interval (a_{j-1}, a_j). The transformation *log(–log(.))* corresponds to the complementary log-log conversion.

3.3 Database and variables

The sample consists of 249 enterprises classified as SMEs in the province of Málaga, observed over a ten-year period from 1996 to 2005. Among these, 128 firms went bankrupt, whereas 121 remained in operation or were dissolved for reasons unrelated to bankruptcy. Based on the censored data, no firm failures occurred before 1999, which ensures that firms surviving fewer than four years were excluded from the analysis.

Because of incomplete regional data for bankrupt companies, national-level information for Spain was used. The source of the economic and financial data is the SABI (*Sistema de Análisis de Balances Ibéricos*) database. The dataset includes 18 variables—nine derived from firms' financial statements and nine binary variables representing qualitative characteristics—yielding a total of 2,047 panel observations.

The dataset is unbalanced, meaning that not all firms are observed for every year. Some companies were dissolved before the end of the study period, whereas others were incorporated after 1996, the initial year of observation.

4. Results

4.1 Descriptive analysis

Table 1 presents the descriptive statistics, including the number of observations, mean, median, standard deviation, range, and coefficient of variation.

None of the variables follow a normal distribution. The coefficients of variation are relatively high, indicating the presence of outliers. Consequently, the median provides a more accurate measure of central tendency than the mean, as the latter is susceptible to distortion by extreme values.

Table 1. Descriptive statistics

Variable	Mean	Median	Min.	Max.	Type	SD	VC
Equity	1,644.6	424.23	-2,733.5	33,432.1	Overall	3,334.2	2.03
					Between	2,869.2	1.74
					Within	1,253.2	0.76
ROA	1.57	3.68	-3,868.7	289.98	Overall	88.0	56.05
					Between	33.4	21.27
					Within	81.6	51.97
Indebtedness	74.5	73.63	1.27	3,712.94	Overall	91.05	1.22
					Between	43.67	0.58
					Within	80.35	1.08
Fixed assets	1,973.4	500.03	0.09	51,178.7	Overall	4,313.5	2.18
					Between	3,604.4	1.82
					Within	1,846.8	0.93
Working capital	1,339.3	642.2	-11,702	62,457.1	Overall	3,186.6	2.37
					Between	2,571.8	1.92
					Within	1,547.5	1.15
Financial result	-51.17	-20.67	-2,111.3	3,312.86	Overall	223.9	4.37
					Between	158.6	3.09
					Within	159.2	3.11
EBITDA	497.08	160.41	-6,943.7	12,494.7	Overall	1,177.3	2.36
					Between	924.7	1.86
					Within	631.3	1.27
Solvency ratio	1.75	1.13	0.00	479.04	Overall	10.7	6.11
					Between	5.1	2.91
					Within	9.4	5.37
Cost of employees over revenue	36.92	20.77	0.09	24,293.9	Overall	537.2	14.55
					Between	172	4.65
					Within	506.3	13.71

SD = standard deviation; VC = coefficient of variation

4.2 Contrast of median differences

Table 2 presents the results of the median test comparing two groups of observations: bankrupt firms and active firms. Because the assumption of normality is not satisfied, the nonparametric Mann–Whitney *Z* statistic is used (Peña, 2008).

For all indicators except debt and personnel costs over revenues, the median is higher for firms that remain active than for those in their final year before bankruptcy. This pattern holds for equity, fixed assets, working capital, financial result, EBITDA, ROA, and the solvency ratio. The opposite relationship is observed for debt and personnel costs over revenues, whose medians are lower for firms that remain active than for those facing bankruptcy.

The test confirms that significant differences exist in the central values of all variables between the operating and insolvency years, except for working capital. The most pronounced differences appear in ROA and EBITDA. Working capital is the only variable that does not exhibit statistically significant median differences.

Table 2. Contrast of median differences

Variable	Dummy	Mean	Median	SD	Z (Mann-Whitney)
Equity	0	1,741.14	476.79	3,409.37	10.073***
	1	197.54	78.37	1,139.25	
ROA	0	5.37	4.06	14.82	12.691***
	1	-55.54	-3.67	343.49	
Indebtedness	0	69.75	72.5	31.75	-9.929***
	1	146.26	92.85	335.87	
Fixed assets	0	2,067.37	547.39	4,428.69	6.403***
	1	565.39	147.55	1,189	
Working capital	0	1,362.21	645.28	3,272.03	0.556
	1	995.61	555.82	1,331.76	
Financial result	0	-49.12	-19.75	226.29	3.707***
	1	-81.96	-34.18	182.39	
EBITDA	0	535.22	179.16	1,191.64	11.107***
	1	-74.7	5.08	731.14	
Solvency ratio	0	1.55	1.14	1.86	4.462***
	1	4.76	0.99	42.25	
Cost of employees over revenue	0	24.24	20.4	29.49	-5.447***
	1	227	31.9	2,144.32	

SD = standard deviation
Dummy variable: 0 = active firms, 1 = bankrupt firms; **p < .01

4.3 Survival analysis

Table 3 and Figure 1 present the results of the survival analysis, showing the number of firms remaining over time and the estimated Kaplan–Meier survival function.

The probability of survival is highest during the fourth and fifth years and decreases steadily thereafter, reaching 48.6% by the ninth and tenth years. The sharpest decline in survival occurs between the sixth and seventh years. From the eighth year onward, the survival curve levels off, indicating that firms that reach this stage tend to develop the financial capacity and industry experience needed to maintain, or only slightly reduce, their probability of survival over time.

Table 3. Estimation of survival function (Kaplan–Meier method)

Period	Sample	Deaths	Censored	Survival Function	SE	95% CI
4	249	1	0	0.996	0.004	0.972 – 0.999
5	248	1	0	0.988	0.006	0.963 – 0.996
6	346	65	0	0.727	0.028	0.667 – 0.778
7	181	46	0	0.542	0.032	0.478 – 0.602
8	135	13	1	0.49	0.032	0.426 – 0.550
9	121	1	0	0.486	0.032	0.422 – 0.546
10	120	0	120	0.486	0.032	0.422 – 0.546

SE = standard error; CI = confidence interval
Survival function estimated using the Kaplan–Meier nonparametric estimator

Figure 1. Estimation of Kaplan–Meier survival function

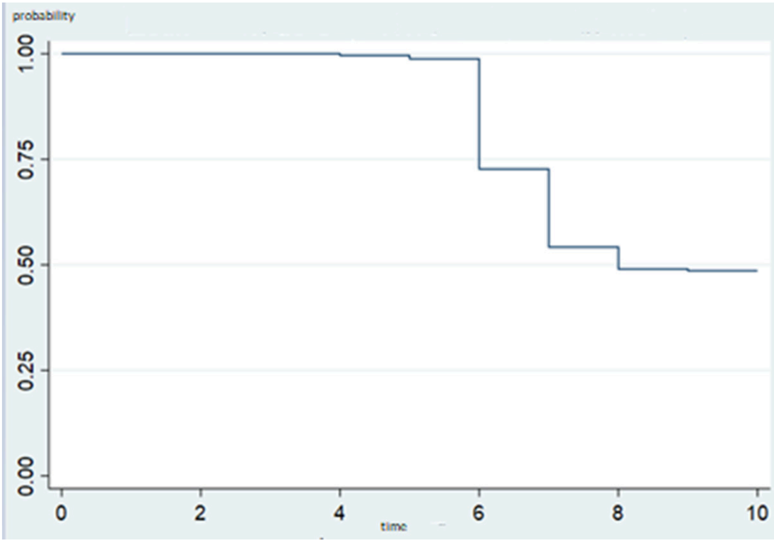
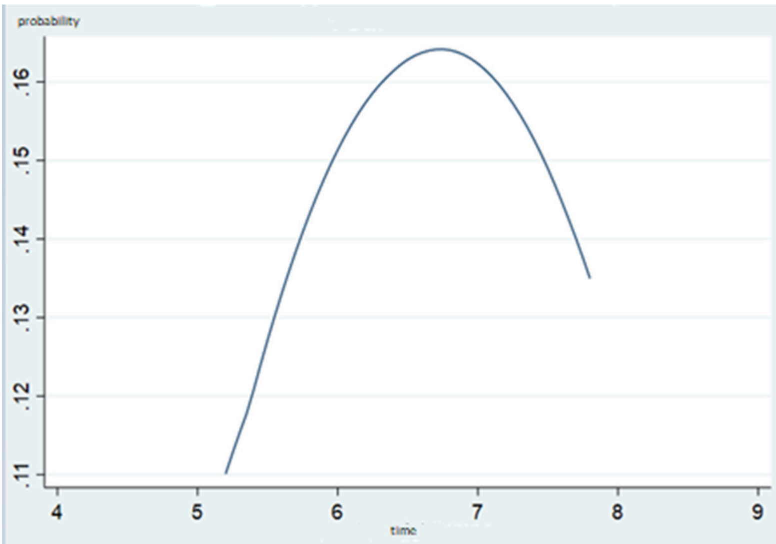


Figure 2 presents the smoothed estimate of the hazard coefficient. From the sixth year onward, the risk of failure increases substantially, reaching its peak during the sixth and seventh years. Shortly after the eighth year, the risk begins to stabilize, indicating that from this point onward, firms maintain a relatively constant probability of failure over time.

Figure 2. Smoothed estimation of the Hazard ratio



4.4 Complementary Log–Log logistic regression

Table 4 presents the results of the complementary log–log (cloglog) logistic regression, showing the ratios and relative weights of the independent variables associated with business failure. The model is statistically significant overall, and all examined factors display a substantial relationship with bankruptcy outcomes.

An inverse relationship is observed for equity, ROA, debt, fixed assets, financial result, and EBITDA, indicating that increases in these variables reduce the probability of bankruptcy (i.e., increase the likelihood of survival). Conversely, a direct relationship is found for working capital, personnel expenses over revenue, and the solvency ratio, meaning that higher values in these variables increase the probability of bankruptcy (or decrease the likelihood of survival).

The hazard ratio indicates the change in the probability of failure associated with a one-unit increase in an independent variable. For the inversely related factors, a one-unit increase in ROA is associated with a 0.00057% reduction in the hazard function, multiplying the probability of survival by 2.65. For equity, fixed assets, and EBITDA, the probability of not failing increases by a factor of 2.72, while for debt and financial result it increases by 2.71.

Among the directly related factors, a one-unit increase in the solvency ratio corresponds to a 0.00745% increase in the hazard function, multiplying the probability of failure by 2.74. Similarly, for working capital and personnel expenses over revenue, the probability of bankruptcy increases by a factor of 2.72.

Table 4. Results of Complementary Log–Log logistic regression

Variable	Coefficient	Hazard Ratio	HR Probability	Z	p
Equity	-0.00057	0.99943	2.717	-3.48***	0.000
ROA	-0.0242	0.97609	2.654	-5.78***	0.000
Indebtedness	-0.00301	0.99699	2.710	-1.90*	0.057
Fixed assets	-0.00022	0.99977	2.718	-2.21**	0.027
Working capital	0.00019	1.00018	2.719	2.36**	0.018
Financial result	-0.00348	0.99652	2.709	-6.01***	0.000
EBITDA	-0.0012	0.9988	2.715	-5.63***	0.000
Solvency ratio	0.00745	1.00747	2.739	10.26***	0.000
Cost of employees over revenue	0.00197	1.00197	2.724	1.91*	0.056

HR = hazard ratio

p values rounded to three decimals

p < .10 (*), p < .05 (**), p < .01 (***)

5. Discussion

This study tested a series of hypotheses concerning the likelihood of SME survival. All examined factors demonstrated statistical significance and predictive power in explaining business failure. However, not all hypotheses were supported: the hypothesis related to working capital did not yield the result anticipated in the literature, whereas the remaining hypotheses were confirmed.

H1, proposing that equity positively influences survival, is supported. Greater equity reduces dependence on external financing and is directly associated with firm longevity.

H2, positing that return on assets (ROA) positively affects survival, is also supported. A higher ROA indicates that investments generate greater profits, which enhances survival prospects. This finding corroborates previous research identifying ROA as a reliable indicator of future cash flows (Ichsani & Suhardi, 2015).

H3, suggesting that gross operating profit (EBITDA) has a positive effect on survival, is confirmed. Higher EBITDA increases the likelihood of survival. Although EBITDA is a strong predictor, it can be legally manipulated by management; thus, its source should be interpreted with caution (Kovacova et al., 2021).

H4, asserting that survival depends positively on an improved financial structure, is supported. The relationship between indebtedness and survival is negative—greater external financing reduces the probability of survival. This finding confirms that sufficient initial resources serve as a stabilizing factor by lowering indebtedness and supporting business development (Castaldo et al., 2023). Furthermore, SMEs' limited bargaining power in accessing credit may lead to structural financial constraints (Bruderl & Schussler, 1990). In the case of the solvency ratio, the relationship is direct: a higher asset-to-liability ratio strengthens survival.

H5, which posits that firm size positively influences survival, is accepted. Fixed assets, rarely used as an absolute measure in prior studies, prove to be a robust indicator of long-term viability.

H6, proposing that the balance between external financial costs and revenues positively influences survival, is also confirmed. This supports the notion that, during periods of high debt repayment, managers may successfully offset costs through returns on external investments—even when reluctant to expose assets to risk (Jackson et al., 2013; Kanatas & Qi, 2005).

H7, which states that survival depends positively on higher human-capital productivity, is accepted. The ratio of employee costs to revenue is a direct indicator of survival. Implementing productivity-based incentive systems may strengthen this relationship while enhancing employee well-being and retention (Verwijmeren & Derwall, 2010).

H8, proposing that working capital positively influences survival, is the only hypothesis rejected. Working capital is inversely related to survival, although it remains a strong predictor. This suggests that a lower volume of liquid assets relative to current liabilities may be advantageous. Excess unproductive cash represents an opportunity cost that limits potential returns on liquid assets. Managers should therefore evaluate excess working capital carefully. This result reinforces the view that negative working capital does not necessarily signal financial distress but must be interpreted in relation to factors such as sectoral and regional conditions (Panigrahi, 2015). Although this finding diverges from much of the previous literature, it aligns with results from certain regions, including Qatar and parts of Africa (Aldubhani et al., 2022; Kabir et al., 2021).

6. Conclusions

6.1 Theoretical implications

This study identifies key financial and managerial factors influencing the survival of small and medium-sized enterprises (SMEs). Using survival analysis based on the nonparametric Kaplan–Meier estimator and complementary log–log logistic regression, the findings confirm that firm survival depends on both structural and managerial elements beyond traditional financial ratios. Financial structure, return on assets, EBITDA, and human capital productivity emerge as positive predictors of business longevity, whereas excessive working capital is negatively associated with survival. These results extend the literature on firm survival by incorporating underexplored variables—such as extraordinary financial results and employee cost productivity—and by linking quantitative modeling with theories of strategic management and organizational performance (Jackson et al., 2013; Verwijmeren & Derwall, 2010).

6.2 Practical implications

The study provides managers and policymakers with evidence-based insights to enhance financial and strategic decision-making. The results highlight measurable performance indicators that can serve as early warning systems to identify vulnerability and prevent insolvency. They also underscore the importance of aligning financial structure and human capital productivity to strengthen organizational resilience and optimize resource efficiency. These implications are particularly relevant for SMEs operating across diverse institutional and economic contexts (Gemar et al., 2019; Serer et al., 2009).

6.3 Limitations and future research

Although the dataset originates from a specific regional context, the methodological framework and variables analyzed are generalizable to a broad range of business environments. Future research could expand this approach by integrating qualitative dimensions such as innovation, digital transformation, and environmental, social, and governance (ESG) factors to deepen understanding of firm resilience in dynamic markets. Cross-country comparative analyses would further strengthen the external validity of these findings and illuminate institutional differences that shape SME survival.

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Data Availability Statement

Available on request from the authors

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