Predicting start-up survival using first years financial statements

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Abstract

Numerous papers demonstrate the usefulness of financial ratios in predicting the bankruptcy of companies, but in the case of new companies their usefulness is questionable. Many of the firms that are successful today made few profits when they were first created. On the other hand, both structural inertia from the theory of organizational ecology and the 'survival of the fitter' principle advocate that companies that are healthy in their early years will go ahead in greater proportion than those that start with many difficulties. Our empirical study used financial data from a sample of 6,167 new-born Spanish start-up companies, analysing their evolution up to eight years later. We found healthier financial indicators in the first years of start-up companies that survived eight years than in those that failed, supporting the organizational ecology theory. We found statistically significant differences in profitability, productivity, liquidity, leverage, and size. The models developed showed predictive capacity, but they did not reach that of the bankruptcy models made with mature companies. The analysed period corresponded to a period of economic crisis. The study was repeated with data from another non-crisis period to enhance the validity of the results, and obtained very similar results.

Keywords: financial ratios, survival analysis, start-ups, bankruptcy, multivariate statistics.

1. Introduction

Numerous empirical studies have demonstrated the usefulness of accounting information to predict the bankruptcy of companies, starting with the pioneering works of Beaver (1966) and Altman (1968). Financial ratios show great predictive capacity, which may be higher than that presented by market variables or other types of variables (Tian et al., 2015). The usefulness of accounting information is questionable in the case of newly created companies, however (Miloud et al., 2012). Many companies have financial problems at the beginning, since their sales and profit figures are often poor, but they become successful. For this reason, some investors do not always pay enough attention to accounting information until a company is mature (Wright & Robbie, 1996). In addition to accounting information, other elements are also widely used in early stage investments, such as dialogues with personnel and unpublished subjective assessments (Jeng & Wells, 2000). The aim of this paper is to investigate the usefulness of financial ratios from the early financial statements in predicting the bankruptcy of start-ups.

The theoretical foundations of our work are based on Hannan and Freeman's (1977) well-known theory of organizational ecology. This theory, which originates in biology, argues that the market causes the disappearance of weak companies through natural selection. This 'survival of the fitter' principle derives from Alchian's (1950) approach. We focus on one aspect in particular, structural inertia, which means resistance to change (Hannan & Freeman, 1984). The structural inertia of companies is a concept borrowed from physics. Physical inertia measures the resistance of any physical object to any change in its velocity and has to do with aspects such as its mass. The greater the mass, the greater the physical inertia, and the less the mobility. The structural inertia of companies has to do with size, age and sector (Hannan et al., 1996; Baron et al., 1999; Colombo & Delmastro, 2002). A large, mature and non-innovative company has great inertia and, therefore, offers great resistance to change. Inertia is the factor that may constrain companies from adapting, which is the point of view in Nelson and Winter's (1982) alternative evolutionary theory of the firm. A related issue is organizational imprinting (Stinchcombe, 1965), which is the initial accumulation of resources provided by the entrepreneur at the birth of the company. Imprinting also favours organizational forms that are relatively stable over time, since the initial conditions create durable imprints on organizations (Stinchcombe 1965).

Financial statements reflect a company's performance and reveal the changes that occur therein over time. The financial statements of mature, large and not very innovative companies will register smaller changes than those of newly created, small and innovative companies. We can expect slight changes in mature companies, as revealed by the financial ratios of Beaver's study (1966), which explained the evolution of financial ratios in bankrupt companies. The deterioration of financial ratios was slow but gradual in most of the indicators, until bankruptcy took place. Small, innovative and newly created companies have less inertia, however, and this greater dynamism and capacity for change should be reflected in their annual accounts, which may have less predictive capacity (Hope, 2013; Miloud et al., 2012). A dynamic start-up could move from a business model based on high profit margins and low asset turnover to the opposite. It could radically change the form of funding, to one that would allow it to maintain losses for years. In fact, many of the successful technology-based companies made losses for years. In this context, it is worth asking about the usefulness of financial ratios from early annual reports. To investigate this premise, we analyse the extent to which accounting information from an organization's first years is useful in predicting its survival. If the premise is not met, young, small and high-tech companies—where lean start-ups abound, with great adaptability (Blank, 2013)—will be able to face changes, at which point scrutinizing their initial accounting information will not be very useful. Our empirical study uses a sample of 6,167 Spanish companies and analyses their evolution up to eight years later. Using accounting data from the second year, we found that companies which survived were already more solvent, more profitable, more liquid, had less debt, were larger, more productive and paid higher salaries than those that did not survive. Although the predictive models developed exhibit a certain predictive capacity, they do not reach that of the bankruptcy models made with mature companies.

Our paper offers novelty with respect to the wider existing literature. Most of the studies that analyse the bankruptcy of companies use mature companies (Camacho-Miñano et al 2015), excluding start-up firms due to data availability (Foreman, 2003), while our work focuses specifically on start-up companies. Works that analyse the survival of new ventures usually analyse qualitative factors, highlighting the characteristics of entrepreneurs, such as Coad et al. (2016), Cheng (2015), Croce et al. (2018), Gartner et al. (1999), and Miettinen and Niskanen (2015). These works tend to study the factors that explain the success of start-ups at the time of their creation (Santisteban & Mauricio, 2017). Our work is different because we analyse start-ups that have been running for a year and already present annual accounts, focusing on the predictive ability of the second year's financial statements. Other works analyse the survival of start-ups using accounting information, such as Laitinen (1992), Huyhebaert et al. (2000), Wiklund et al. (2010), Laitinen (2017), or Dosi et al. (2017), among others. Wiklund et al.

(2010) and Dosi et al. (2017) do not focus on the predictive capacity of models, so they do not provide calculations such as accuracy, true negative and true positive rates. Our study tries to move from a descriptive approach to a predictive one (Taagepera, 2008). We divided the sample into two subsamples, the training sample and the test sample, applying various techniques (logistic regression, neural networks and CHAID decision trees) and calculating performance measures such as accuracy, true negative and true positive rates. The papers most similar to ours are those by Laitinen (1992 and 2017). These papers both revealed that it is already possible, to some degree, to predict the failure of a newly founded firm in the first year after foundation. Their samples of companies contained only 20 and 29 failed companies respectively, however, while our work analyses all the high-tech industry and knowledge-intensive companies created in Spain in 2007. Our work also uses advanced machine learning techniques to improve prediction.

The paper's contribution is threefold. First, using data from the second year financial statements, we found that the companies which survived presented better values in their financial ratios than those that did not survive. Secondly, those differences are not diluted over time but affect the survival of the company up to at least eight years later. For example, the risk of bankruptcy for companies that are unprofitable after one year of life is 1.625 times higher than for profitable firms, and this result is highly significant. Thirdly, the models developed have some predictive capacity, although this capacity does not reach the predictive capacity presented by the models carried out with mature companies. The results reveal that the companies which are not aligned with the environment in their early years, which is indirectly revealed by presenting poor financial figures, will probably not develop that alignment in future years. A possible explanation for this is the presence of structural inertia. Organizations have high inertia when the speed of reorganization is much lower than the rate at which environmental conditions change.

These findings present interesting practical implications, since investors would do well to analyse the annual statements after foundation. If a newly created company already presents good values in the main financial indicators, it is more likely to survive than those that present difficulties. This does not mean that they should only focus on accounting information, however, since predictive models show that much remains unexplained. The rest of the research is organized as follows. Section 2 presents the literature review and the hypothesis development. Section 3 displays the empirical study. Finally, discussions and conclusions are presented in Sections 4 and 5.

2. Literature Review and Hypothesis

We conducted the literature review using bibliometric analysis to identify the most relevant articles. The literature search included two elements: start-ups research and financial distress prediction. We selected articles by searching keywords through the Web of Science. The following search criteria were entered into the Web of Science database: [TS=("new firms" OR "startup*" OR "start-up*" OR "new-born firm*" OR "new venture" OR "venture capital") AND TS=("bankruptcy" OR "firm failure" OR "business failure" OR "financial distress" OR "failed firms" OR "survival")]. The bibliographic search was completed by reading several literature reviews (Alaka et al., 2018; Coad, 2009; Pardo del Val & Martínez Fuentes, 2003; Santisteban & Mauricio, 2017; Schwarz et al. 2018; Spender et al., 2017; Sun et al. 2014; Tian et al., 2015).

Numerous theories try to explain the growth and survival of companies (Coad, 2009). One is the theory of organizational ecology by Hannan and Freeman (1977). Three concepts from this theory are relevant to this paper: structural inertia, imprinting and the 'survival of the fitter' principle. Pardo del Val and Martínez Fuentes (2003) and Schwarz et al. (2018) provided reviews of the literature on structural inertia, a persistent organizational resistance to change. Inertial forces vary over the life cycle (Hannan and Freeman, 1984). Hannan et al. (1996) studied inertia and change in an organization's early years using a sample of young, high-technology firms, concluding that initial conditions matter a great deal for organizations, even within the turbulent early years. In other words, origins matter. Some empirical studies, such as Ruef (1997) or Kelly and Amburgey (1991), confirmed the existence of inertia, supporting the prediction that old organizations are less likely than young ones to experience change in their core features. However, other studies do not find empirical support for the inertia hypothesis, such as Guillén (2002), who found that inertia does not play a role in foreign expansion processes. Organizational imprinting can be defined as a process whereby, during a brief period of susceptibility, a focal entity develops characteristics that reflect prominent features of the environment, and these characteristics continue to persist despite significant environmental changes in subsequent periods (Marquis & Tilcsik, 2013). Finally, the 'survival of the fitter' principle, which applies the Darwinian idea of evolution of the species to companies, advocates that firms which are healthy at the beginning will survive in greater proportions than those which start with many financial difficulties (Coad, 2007).

Spender et al. (2017) review recent literature on start-up companies, highlighting among topics of interest, their growth (Coad, 2009), financial structure (Cotei and Farhat, 2017), and critical success factors (Santisteban & Mauricio, 2017). Newly created companies have a higher failure rate than established ones (Jones, 1987), so bankruptcy studies and success factors are particularly relevant. Cader and Leatherman (2011) found that more than 40% of firms did not survive after three years; Phillips and Kirchhoff (1989) found that three out of five new businesses close in the first five years; and Knaup and Piazza (2007) found that about 40% of firms did survive after five years. Rannikko et al. (2019) found that 72% of new technology-based firms survived after eight years, although very few companies experienced high-growth during their first seven years.

Sun et al. (2014), Tian et al. (2015), and Alaka et al. (2018) provided literature reviews of financial distress predictions. Among the topics that are still discussed today, the definition of failure stands out, as well as selection of the predictive variables, the statistical techniques used, the methodology used to perform the empirical studies, and the theories that support the findings. Ohlson (1980) adopted a purely legalistic definition of bankruptcy, however, Kahya and Theodossiou (1999) argued that many healthy companies filed for bankruptcy for reasons other than financial distress, such as avoiding taxes or lawsuits. Conversely, financially distressed companies do not always legally fail because they are absorbed or merged with others. Kahya and Theodossiou (1999) selected their sample of failed companies based on debt default criteria for all these reasons. Shumway (2001) went beyond a dummy variable that measures success or failure, considering 'time to failure' as the dependent variable, instead of 'failure'. Given the difficulty of agreeing on a definition of failure, Sun et al. (2014) proposed that various degrees should be used, such as mild, intermediate, and bankrupt.

Numerous indicators have been proposed to predict bankruptcy, but financial ratios prevail. Tian et al. (2015) analysed 39 bankruptcy predictors, finding that classical financial ratios provide significant additional information about future failures beyond market-based variables. Of all financial ratios, Lukason and Laitinen (2019) found that annual and accumulated profitability are the most important failure risk contributors. Agarwal and Taffler (2007), and Altman et al. (2017) show the persistence over time of bankruptcy prediction models based on the use of accounting information. The statistical techniques used have evolved from linear discriminant analysis (Altman, 1968) to the use of advanced machine learning techniques, including ensemble techniques, dynamic modelling, and modelling with group decision-making techniques (Sun et al., 2014). Training sampling and testing sampling are the most popular methods for sampling, using both balanced and imbalanced sampling (Sun et al., 2014). Finally, the fact that many developments are only based on statistical theory, and not on formal theory, and are thus mere pattern recognition devices has been criticised (Agarwal & Taffler, 2007). Authors such as Gordon (1971), Scott (1981), and Purnanandam (2008), however, have developed explanatory theories of corporate bankruptcy.

Finally, the literature review also served to identify avenues for research. Table 1 summarizes the main studies on success factors in the survival of start-ups. After reading the literature reviews by Santisteban and Mauricio (2017) and Spender et al. (2017), we grouped the determinants of start-up survival into several categories: firm peculiarities, environmental factors, organization strategy, financial performance, financial slack, and human capital. The literature review reveals that the role of leverage is not clear, since some authors argue that bank debt is an indication that a start-up is promising (Robb & Robinson, 2014), although debt increases the risk (Laitinen, 1992; Cressy, 1996; Huynh et al., 2010). Few papers present empirical evidence about the role of liquidity in start-ups; one is Wiklund et al. (2010). The talent of the employees is an important factor, usually measured by training and experience; however, we propose to use the average salaries of the employees as a proxy, calculated from accounting statements. There are abundant studies analysing size and profitability (Mata, 1994; Geroski, 1995; Laitinen, 1992; Wiklund et al. 2010), and the results are clear. We need both indicators to develop the predictive model.

** Table 1 to be inserted here **

2.1 Hypotheses development

The size of the company is a factor to consider regarding success even within small companies. The organizational ecology theory predicts a positive relationship between company size and survival because organizations undergoing structural transformation are highly vulnerable to environmental shocks, and a larger size enhances an organization's capacity to resist environmental shocks (Hannan & Freeman, 1984). Most start-ups begin small, and small businesses suffer from the liability of smallness, meaning that there is a positive relationship between survival and size (Aldrich & Auster, 1986). Aldrich and Auster (1986) identified several factors that make survival problematic for small organizations, whether they are new or old. Tax laws work against the survival of small organizations, government regulation weighs more heavily on small than on large organizations, and small organizations face major disadvantages when competing with larger organizations for labour. Moreover, the access of small companies to bank financing is limited, which coincides with the study by Bernanke and Gertler (1995). Bernanke and Gertler (1995) found that the access of small companies to the credit markets is more limited than for large companies, and they are more likely to go bankrupt. The presence of industry-specific experience and entrepreneurial experience has a positive effect on start-up size (Furlan, 2019), which increases the probability of survival. In summary, Bercovitz and Mitchell (2007) reviewed twenty years of research, showing that larger companies tend to survive longer than smaller companies. In other words, the bigger, the better (Santisteban & Mauricio, 2017). Consequently, the following hypothesis is proposed:

Hypothesis 1: A start-up's probability of bankruptcy decreases as the firm's size increases.

Reaching the threshold of profitability is an important milestone for newly created companies, since not all have profits in their first years. In fact, positive profits can be seen as the natural selection criterion (Penrose, 1952). The environment selects companies that achieve profits, while other companies are excluded and eventually disappear. The theory of organizational ecology assumes that, given natural selection, efficient companies that maximize profits will survive and dominate. Alchian (1950) argued that through a process of economic natural selection, firms who realize positive profits survive, while those who suffer losses disappear. The 'survival of the fitter' evolutionary principle suggests that companies which are healthier at birth survive in greater percentages than the unhealthiest ones, which should be reflected in their early financial statements. Coad et al. (2016) examined whether, as a new venture ages, it becomes easier to predict both survival and sales growth, finding that the sales growth of a new venture approximates a random walk, while its survival becomes more predictable. Laitinen (1992, 2017), Fotopoulos and Louri (2000), Wiklund et al. (2010) and Delmar et al. (2013) found empirical evidence highlighting the importance of profitability ratios in the early stages of a start-up. Consequently, the following hypothesis is proposed:

Hypothesis 2: A start-up's probability of bankruptcy decreases as the firm's profitability increases.

Start-up companies that intend to grow seem more likely to use bank financing; in addition, these companies have incentives to establish credit relationships with financial institutions as soon as possible (Cassar, 2004). If a bank has granted a loan, it is usually a good sign that a start-up is promising (Robb & Robinson, 2014; Cole & Sokolyk, 2018). However, indebted companies go bankrupt in greater proportions than those which maintain a balanced net worth figure (Lang et al., 1996; Fotopoulos & Louri, 2000). Leveraging increases the riskiness of the firm, and the theory of organizational ecology offers explanations for the positive relationship between debt and failure. A run of very bad years for a company, in combination with an unfavourable environment, produced, for example, by the presence of an economic crisis, might actually find a highly levered firm unable to meet its debt service requirements, leading to bankruptcy (Miller, 1988). The liability of newness is explained by the accumulation of knowledge, skills, and the growing consistency of organizational behaviour over time (Freeman et al., 1983). Altman (2013) pointed out that young companies fail in greater proportions than mature ones, because they do not have time to construct their cumulative earnings. If a company has profits and does not distribute them, they become part of the reserves, which increases the net worth, but if the company has losses, the net worth decreases. In this way, retained earnings provide a measure of the financial and operational performance of a company since its inception, serving as an indicator measuring the distance to bankruptcy (Akerlof & Shiller, 2010). Debt can be a problem if the percentage of debt is high with respect to net worth or assets, revealing a lack of capital strength. Consequently, the following hypothesis is proposed:

Hypothesis 3: A start-up's probability of bankruptcy increases as leverage (interest coverage) increases (decreases).

Sometimes profitable companies with low levels of debt fail due to a lack of liquidity. Environmental conditions play a major role in affecting organizational outcomes (Tushman & Anderson, 1986). According to the theory of organizational ecology, when the environment declines significantly, a company increases its chances of survival if it has enough working capital. Working capital is the amount of cash and other current assets a company has available to pay its short-term expenses. An organization, even a weak one, can survive as long as its environment is benign. At some point, however, the environment may shrink in its carrying capacity or shift in the requirements it places on organizations (Hambrick & D'Aveni, 1988). Death may occur if a firm's environment declines meaningfully and the firm's liquidity deteriorates sharply. Working capital thus gauges a firm's cushion for meeting immediate resource needs. The empirical study by Hambrick and D'Aveni (1988) confirmed the deterioration of working capital in the years immediately before bankruptcy. The empirical study by Wiklund et al. (2010) on the survival of start-ups also found that higher liquidity was associated with lower odds of failure.

Working capital can also be used to estimate the ability of a start-up to grow quickly. If a firm has considerable cash reserves, it may promptly scale up the business. A better financial capacity gives the start-up better agility in changes of product and technology, thus resulting in a better adjustment to client demand (Santisteban & Mauricio, 2017). Finally, sometimes it is even early success characterized by excessive growth, with many requests to attend, accompanied by the growing needs of working capital, which can lead to bankruptcy. Garnsey (1998) described cases of companies with liquidity problems (due to the need for more working capital for development and for more materials and staff), which led to bankruptcy. Consequently, the following hypothesis is proposed:

Hypothesis 4: A start-up's probability of bankruptcy decreases as the firm's liquidity increases.

The environmental ecosystem of start-ups is characterized by an uneven distribution of scarce resources, which include sources of capital such as those provided by venture capitalists, and a talent pool of knowledgeable professionals and skilled employees, universities, professional services, and technologically savvy customers (Zacharakis et al., 2003). The spinouts created in this environment attract knowledgeable professionals. One feature of successful high-technology firms is that their founders provided an organizational imprinting for the construction of organizations, many with the imperative to capture the most talented individuals (Baron et al., 1996). In fact, the success of a company often reflects its ability to combine talent, generating a team capable of working in coordination (Ensley et al., 2002).

Start-ups disproportionately employ and hire young workers: around 27% of employees in firms aged one to five years are between 25 and 34 years old, a percentage that exceeds 18% of mature companies (Ouimet & Zarutskie, 2014). Promising start-ups attract talent: the best-qualified young workers are attracted to young companies where they can make a career. They select those companies that are more likely to survive and achieve success (Acs et al., 2007). It is difficult to measure talent with accounting information, but salaries can be a proxy, and in fact, young employees in young firms earn higher wages than young employees in older firms (Ouimet & Zarutskie, 2014). Dosi et al. (2017) found empirical evidence for the 'survival of the fitter' principle in the case of labour productivity, albeit modestly. Earlier studies found human capital to be a good predictor of the survival of new firms (Cooper et al., 1994; Gimeno et al., 1997; Geroski et al., 2010). Consequently, the following hypothesis is proposed:

Hypothesis 5: A start-up's probability of bankruptcy decreases as the firm's human capital development increases.

3. Empirical Study

3.1 Sample and data

Not all new companies are start-ups; these entities are characterised by their ability to create a new product or service under conditions of extreme uncertainty (Ries, 2011). For Luger and Koo (2005) a start-up is a new business entity, which starts hiring at least one paid employee during the given time, and which is neither a subsidiary nor a branch of an existing firm. Other authors emphasize that, in addition to all of the above, start-up companies are necessarily engaged in innovation processes (Spender et al., 2017). An approach to identifying companies that are start-ups in a database is to identify young companies, belonging to the sectors that are considered most innovative. We considered three options: young innovative companies (YICs), new technology-based firms (NTBFs), and high-tech industry and knowledge-intensive services (HTEC).

Young innovative companies (YICs) are new, small, and highly research and development (R&D)-intensive enterprises. This approach analyses annual accounts and calculates the percentage of R&D expenses of a company's total operating expenses. It is generally accepted that the R&D expenses of a company should represent at least 15% of its total operating expenses, that it must be less than six years old, and have fewer than 250 employees (Czarnitzki & Delanote, 2012). New technology-based firms (NTBFs) are independently owned companies established for exploiting an invention or technological innovation, having substantial technological risks, and no more than 25 years old (Little, 1979). It is not always easy to identify these companies in practice because the definition is not precise enough (Czarnitzki & Delanote, 2012). In fact, authors such as Rannikko et al. (2019) studied NTBF but used the classification proposed by the statistical office of the European Union (Eurostat, 2016) to identify HTEC companies. Two main approaches can be used to identify HTEC: the sectoral approach and the product approach. The sectoral approach is an aggregation of the industries according to technological intensity based on the European Classification of Economic Activities (NACE) classification code at 2-digit level. The product approach is based on the calculations of research and development intensity by groups of products on the basis of the Standard International Trade Classification (SITC). We chose to analyse HTEC using the sectoral approach, for the confidence it gives in performing a company search in a database according to the NACE code list, provided by an official source (Eurostat, 2016). The study is thus easily reproducible in other countries.

The sample of companies for the empirical analysis comprised all the companies created in 2007 in Spain whose main activity fits into one of those sectors according to Eurostat (2016). The data came from the Spanish database SABI, distributed worldwide by Moody's, which takes accounting information from the National Commercial Register (Spanish Companies House) and non-financial information from other official sources. SABI is a historical database that maintains company data even if a firm did not report anything in the last years. Private firms face different financial disclosure regulations around the world; for example, most US private companies are not required to file financial data at all (Minnis & Shroff, 2017). In contrast, it is compulsory for all Spanish companies to disclose their annual accounts in the National Commercial Register, which is a public register. Table 2 shows the sectors analysed and the number of companies in each, a total of 6,167 companies. As peculiarities of the Spanish case, it is worth noting the small size of the companies, since most of the Spanish companies are micro-enterprises. Beyond this, and being HTEC start-up companies, we think that there is no reason to expect that many differences from similar companies in other countries—that is, they are usually small, innovative companies, with young and well-trained employees, created by entrepreneurs who stand out for their training and professional experience (Storey & Tether, 1998). We therefore think that the results could be extrapolated to other contexts.

** Table 2 to be inserted here **

The first year's financial statements (2007) barely revealed economic activity for many companies, especially those created at the end of the year. We conducted a study to see if it made sense to use the accounting information from 2007. We calculated Spearman's correlation coefficient between the date of foundation of the company (previously converted to an integer) and the return on assets (ROA) of each year. The correlation coefficient between the date of creation and the ROA of the first year was -0.128, negative and statistically significant. This implies that the companies created at the end of the year were less profitable than those created in the first months, which is logical because they had little time to make profits. No differences were found for the other years. To minimize bias, we did not consider the annual statements of 2007 but those of 2008; and thus we analysed the second year financial report.

The SABI database not only provides accounting data but also company status—that is, if a company went bankrupt, together with its status change date. A firm was considered as failed if it had entered statutory bankruptcy proceedings, both voluntary and compulsory liquidations. When a company cannot pay its debts, managers can present a voluntary liquidation to the judge, or creditors can present an insolvency request to the judge, the voluntary liquidation being the most common situation by far in Spain (Camacho-Miñano et al., 2013). Most companies are usually liquidated after bankruptcy but sometimes they are also successfully reorganized. Unfortunately, few companies manage to reorganize after a bankruptcy: 5% in Spain, 2% in the UK, 4% in Italy and 12% in France; the latter has legislation that is very favourable to business continuity (Celentani et al., 2010). Although the SABI database provides company status, we carried out a manual control, verifying the existence of annual accounts during the years after bankruptcy, a sign of reorganization.

In the first part of the study the dependent variable is a dummy variable that assigns the value 1 if the company was solvent in the year 2009 and a 0 if the company was bankrupted. Those companies that went bankrupt so quickly that they did not present annual accounts were discarded from the sample. Many bankruptcy studies analyse five years, from Beaver's pioneering work (1966), although others examine up to seven years prior to the bankruptcy event (Rose & Giroux, 1984). Rannikko et al. (2019) studied the survival of new technology-based enterprises that survived after eight years. They found that very few companies experienced high-growth during their first seven years, so we think it is appropriate to use long terms. In our case, we selected the companies created in 2007, we examined the annual accounts of the year 2008, and we analysed whether they went bankrupt for another seven years, from 2009 to 2015. We therefore analysed eight years after the foundation of the company. Table 3 shows the percentage of companies that went bankrupt and survived annually. Each year, on average, 7.25% of the sample goes bankrupt, which means that at the end of the years analysed, the survival rate was 49.24%.

** Table 3 to be inserted here **

Table 4 shows the financial ratios used. Total assets (TA) was selected for the first hypothesis about firm size. Another option was to use the number of employees as size proxy. We made the calculations using the number of employees, and the results were very similar. Two indicators were selected for the second hypothesis on profitability: return on assets (ROA) and a dummy variable equal to 1 if the firm has profits (PROFIT). Beaver et al. (2012) included the same dummy variable in their bankruptcy prediction model, arguing that the indicator variable permitted different intercepts and different slopes for loss versus non-loss firm-years. Four financial ratios were selected for hypothesis three on debts-problems, which measure the percentage of debt (TL/TA), the sufficiency of the profits to face the payment of interest (ICR and DCR), and cash flow to total liabilities ratio (CF/TL). It should be noted that interest coverage ratio (ICR) presents many problems when a company has no interest expense. We replace it with the value that arises from the winsorization of the financial ratio. A company that has no interest expense obtains a value of the ratio equal to that obtained by the companies that have the maximum coverage. In our case, that value was 30.

Hypothesis four about liquidity was measured with three variables: the working capital ratio (WC/TA), the cash ratio (CR), and a dummy variable equal to 1 if the firm's working capital is positive (WC). A negative working capital may indicate the presence of financing constraints, as firms whose current liabilities are higher than their current assets may be unable to pay back creditors in the short term. In other words, it is a symptom of insufficient liquidity, which can lead to bankruptcy (Ding et al., 2013). The cash ratio measures short-term liquidity and is calculated by dividing the amount of cash and cash equivalents by the amount of current liabilities. Finally, hypothesis five on a firm's employee talent was measured using two financial ratios, productivity (R/E) and costs of employees (C/E).

** Table 4 to be inserted here **

3.2 Methodology

We tried to use the most appropriate statistical technique for each study. First, an exploratory analysis was completed with a non-parametric Mann-Whitney test. Survival analysis was then used to test the hypotheses, analysing whether differences in a start-up's second year financial statements are able to explain the bankruptcy or survival of the company up to eight years after its creation. We performed a Cox regression analysis, whose independent variables were the financial ratios of the second year, and the dependent variable was the number of days that the companies manage to survive, up to a maximum of eight years.

Some authors argued that predictive models were merely empirical and had no theory behind them (Gambling, 1985). Other authors replied that sometimes the developed models validated a set of hypotheses but were useless for prediction (Taagepera, 2008), and one of the central issues in the academic literature on entrepreneurship focuses on criteria for predicting successful new ventures (Gartner et al., 1999). We believe that both approaches can be complementary and not exclusive; this is a line of work initiated by Scott (1981), who argued that bankruptcy prediction is both empirically feasible and theoretically explainable. Advanced machine learning models will be used for this purpose, (Alaka et al., 2018). We used techniques such as logistic regression, neural networks and CHAID decision trees to achieve the best prediction performance. This part of the study assesses the extent to which the financial information of newly created companies can be integrated into models that predict whether a company will fail, which is really useful for making decisions. To do this, the sample was divided into two subsamples, the training sample and the test sample. The train sample was paired, following the usual practice of many studies, in which the number of bankrupt companies is the same as that of the non-bankrupt companies (Zhou, 2013). A series of univariate logistic regressions was carried out, using a single variable in each model.

3.3 Results

Table 5 shows the results of the exploratory analysis: the mean, median and standard deviation of the variables for the year 2008. The results of the two groups are presented, one with the companies that went bankrupt the following year, that is, in 2009, and the other with the non-failed firms. The table presents the statistics without eliminating outliers or transforming the data. The high standard deviation in many ratios is particularly striking, indicative of a great deal of dispersion. Note that the mean and the median sometimes have very different values, a sign that the distributions are not symmetric. The existence of extreme values, asymmetry and absence of normality are common in accounting information (Ezzamel et al., 1987), but the table shows that it is remarkable in the case of newly created companies. Several alternatives have been proposed to deal with such distributional problems: removing outliers, transforming the data or using robust statistical techniques (Ohlson & Kim, 2015). We have chosen not to eliminate outliers, but to winsorize the data by setting the observations below the first and above the 99th percentile of the distribution to the values at the first and 99th percentiles (Barber & Lyon, 1996).

** Table 5 to be inserted here **

Table 5 shows the results of a non-parametric Mann-Whitney test to detect whether the differences are statistically significant; the appropriate test for the dummy variables is Pearson's chi-square test. Mann-Whitney tests indicated that non-failed start-ups are larger than those that failed, and the differences are statistically significant. Non-failed start-ups are more profitable than those that went bankrupt, and the differences are statistically significant. Non-failed start-ups have less debt than those that went bankrupt, and the differences are statistically significant. Non-failed start-ups have more liquidity than those that went bankrupt, and the differences are statistically significant. Non-failed start-ups have better labour performance than those that failed, and the differences are statistically significant.

The results obtained through the non-parametric Mann-Whitney test are in line with expectations, and we then performed a survival analysis to confirm the hypotheses. Table 6 shows beta coefficients, significance and the hazard ratio Exp(B). The regression coefficients estimated for all variables were significant. In other words, the financial ratios of the newly created companies reveal symptoms that can explain the survival of the companies up to eight years later; hence, H1 to H5 are accepted, in the analysed data. For example, the risk of bankruptcy for start-ups that are unprofitable after a year of life is 1.625 times higher than for profitable firms, and this result is highly significant (p-value<0.000). The hazard ratio is 1.399 where the start-up has positive working capital. In the case of continuous variables, Exp (B) represents the predicted change in the bankruptcy hazard for a unit increase in the predictor. Debt ratio presents the highest hazard ratio (2.311, p-value<0.000). As the debt increases, after controlling for other variables, the probability of bankruptcy increases. Conversely, the cash flow to liabilities ratio shows the lowest hazard ratio (0.401, p-value<0.000). As the ratio increases, the probability of bankruptcy decreases. In summary, the research confirms that financial indicators of newly created companies have a significant impact on the probability of firm failure up to eight years later. The analysed data supports the 'survival of the fitter' principle, and healthy start-ups in the beginning go ahead in greater proportions than those that suffer difficulties from the beginning.

** Table 6 to be inserted here **

Beyond finding statistically significant differences, our next empirical study tries to develop predictive models and contrast their accuracy. We performed 12 univariate logistic regressions for predicting bankruptcy, one for each variable. Table 7 shows the regression coefficients and reveals that they are statistically significant. Several measures of performance accuracy were used: accuracy, true negative rate, true positive rate, and AUC, which is the area under the receiver operating characteristic (ROC) curve. Most of the variables display a low predictive power, with accuracies that barely exceed 50%. The variables that best predict the crisis are PROFIT, which measures whether the company had profits or not, and WC, which measures whether the working capital was positive or negative. In the first case, the accuracy of the test was 63%, with a true negative rate of 57.4% and a true positive rate of 63.2%. The continuous variables also showed predictive power; for example, the cash flow to liabilities ratio index obtained an accuracy of 67.1%, a true negative rate of 53.4% and a true positive rate of 67.5%.

** Table 7 to be inserted here **

Multivariate predictive models were developed. Several techniques were used: multivariate logistic regression, a CHAID decision tree and two models of neural networks: multilayer perceptron (MLP), and radial basis function (RBF). Table 8 shows the accuracy, true negative rate, true positive rate and AUC. Figure 1 shows the ROC curve. The multivariate models improve the univariate model results notably. The highest accuracy, 69.9%, was obtained with an MLP neural network. The results reveal some predictive power, but far from that of the classic models applied in mature companies.

** Table 8 to be inserted here **

** Figure 1 to be inserted here **

3.4 Validation

To ensure the validity of the results and their generalization, we carried out a new study with companies created in 1999, whose data extended to 2006. We chose this period as prior to the crisis in Spain, which began in 2008. According to the Statistics of Liquidations and Insolvencies of the Spanish Institute of Statistics (INE, 2019), some 7,000 companies went bankrupt every year during the crisis period, while in the non-crisis period that figure did not usually exceed 1,000 companies. We thus analysed two periods, with and without crisis.

The results are shown in several annexes. First, the exploratory analysis is shown, specifically the results of a Mann-Whitney U test and a Pearson's chi-square test in the case of the variable dummy (Annex 1a). The survival analysis was also replicated, by means of Cox regression (Annex 1b). The five hypotheses were equally accepted, in the new data analysed. Annex 1c displays univariate logistic regressions analysis for predicting bankruptcy Annex 1d shows the predictive capacity of a multivariate logistic regression, MLP and RBF neural networks, and CHAID Decision Tree. The accuracy is very similar using the new data.

** Annexes to be inserted at the end of the paper **

4. Discussion

We argue that it is worth analysing the early financial statements of HTEC start-up companies and creating mathematical models that are good enough to predict their survival. The theory of organizational ecology by Hannan and Freeman (1984) provided the theoretical framework, particularly the concepts of structural inertia and imprinting, and the 'survival of the fitter' principle, however, it is also possible that the structural inertia of start-up high-tech companies is low, due to their youth, size and the sector in which they operate, demonstrating a great adaptability that makes it useless to look at the annual accounts. This would explain the low use of financial information by venture capitalists when evaluating new investments (Smolarski et al., 2011); because the value of financial statements is considered to increase as firms mature (Hand, 2005). Our empirical study finds that it is worth analysing the accounting information of companies that have been in operation for barely a year. New companies whose financial statements showed profitability, little debt, liquidity, a certain size and the ability to capture talent showed the highest survival rates. We analysed the Spanish HTEC industry, an innovative sector with has the greatest adaptability and the least inertia. In this dynamic sector, the role of structural inertia is doubtful. Out findings contribute modestly to the theory of organizational ecology, validating both structural inertia and the 'survival of the fitter' principle even in this sector. We believe that the results could be extrapolated to other less dynamic sectors.

The paper also sheds light on the debate about the usefulness of financial versus non-financial information in the case of start-ups. Venture capitalists do not always analyse accounting information in their investment decision making; they examine variables such as the quality of the founder and top management team, the attractiveness of the industry, and product differentiation (Miloud et al., 2012). In fact, although financial statements are the type of information most requested by banks, Minnis and Sutherland (2017) found that banks required financial statements from only half of small borrowers. It is assumed that the accounting information of small private companies is of low quality (Hope, 2013), because it is not normally audited and there are many possibilities for creative accounting, however, accounting information may play an important role in start-ups because it facilitates transactions between financiers and those who require financing (Christensen et al., 2016). The role of accounting information versus information relating to entrepreneurs in order to raise funds varies between countries, with the financial orientation of the investor also being relevant (Manigart et al., 2000). Better financial reporting quality increases the access of private firms to debt financing and lowers their cost of debt (Ding et al., 2016). Finally, it must be borne in mind, that accounting information not only reveals financial performance, but also aspects related to the strategy followed by the company—for example, information on margins, capital structure, or the remuneration of employees, aspects that also determine their survival. Our paper shows that even the accounting information of these companies can be good enough to predict, in many cases, their future bankruptcy.

The paper also contributes to the debate on the role of leverage in start-ups. The leverage-irrelevant proposition by Modigliani and Miller (1958) argued that the market value of any firm is independent of its capital structure, but this theory is based on many assumptions that are not always met by small start-ups. Having bank financing can be seen as a sign that a company has passed the filter of financial institution solvency (Cooper et al., 1994; Robb & Robinson, 2014; Cole & Sokolyk, 2018). Our results indicate that the higher the debt, the lower the probability of survival, however, in line with other studies (Laitinen, 1992; Cressy, 1996; Fotopoulos & Louri, 2000; Huynh et al., 2010; Wiklund et al., 2010). Our paper also highlights the importance of liquidity, measured by working capital divided by total assets, and by the cash ratio. Bankruptcy prediction models have incorporated these indicators, both classic models (Altman, 1968) and recent ones (Altman et al., 2017), but they are not often used in studies of the survival of start-ups. We agree with Wiklund et al. (2010) that liquidity variables should be used to analyse the solvency of start-ups, and our study found that they have great predictive power.

These findings have interesting practical implications. Some investors enter the capital of the company in the early rounds with the goal of exiting sooner rather than later. Venture capitalists will be more likely to have a successful exit outcome if they mitigate information asymmetries (Cumming & Johan, 2008), and quality accounting information helps reduce information asymmetries (Biddle & Hilary, 2006). Other investors have a long-term vision, with an interest in knowing whether the accounting information of this early stage explains the survival of the company several years later. The degree of asymmetric information has a significant impact on the time-to-exit (Gompers, 1995), which implies that early stage investments require a longer lasting involvement of funds than later-stage ones, since asymmetric information decreases over time (Giot & Schwienbacher, 2007). Analysts and investors would do well to analyse the accounting information of start-up companies. The predictive capacity of the financial ratios of start-ups is lower than that presented by mature companies, but it is still considerable.

This paper has several limitations. The financial statements for the first year are not reliable enough if a company was created at the end of the year. Perhaps the profit obtained in one month could be extrapolated, but it is worth continuing to analyse this, with new studies to investigate the usefulness of the first financial report. On the other hand, a single database was used, with data from Spanish companies from a single sector, high-tech industry and knowledge-intensive companies. Two different periods were analysed, one corresponding to a period of crisis and one of growth, but it would be good to extend the study to other sectors and countries. There may be start-up companies whose NACE code does not belong to the list provided by Eurostat (2016), as there may also be newly created companies from those sectors that do not fit the definition of start-up. We recognize that it is another limitation, although using the Eurostat codes (2016) allows the reproducibility of the study.

The analysis could be extended to other homogeneous industries, such as electronic commerce, biotech or social entrepreneurship, as a future research direction. This would allow other accounting variables to be added, such as margins, and assets turnovers. Finally, although the techniques used are among the most commonly used models, it is worth considering the use of data mining techniques that could improve accuracy.

5. Conclusions

This paper aimed to test whether it is worth analysts and investors, especially venture capitalists, analysing the accounting information of companies that have been in operation for barely a year, or if that accounting information does not contribute anything. The theory of organizational ecology provides the theoretical support for our hypotheses; this theory applies the Darwinian ideas of the evolution of the species to companies, arguing that healthy companies at the beginning will continue in greater proportions than those which start with many difficulties. The empirical study was carried out analysing a sample of 6,167 Spanish start-ups belonging to the high-tech industry and knowledge-intensive services. Using accounting data from the second exercise, we have found first that the companies which survived were already more solvent, profitable, had more liquidity, less debt, were larger, more productive, and offered higher salaries than those who did not survive, and the differences are statistically significant. Secondly, we performed a survival analysis using Cox regression, finding that these differences are not diluted over time, but affect the survival of the company up to at least eight years later. For example, the risk of bankruptcy for companies that are unprofitable after one year of life is 1.625 times higher than for profitable firms, and this result is highly significant. Thirdly, logistic regression, neural networks models and CHAID decision tree models were undertaken, finding that the developed models have some predictive capacity, although the capacity does not reach that presented by the models made with mature companies. The data analysed supports the ‘survival of the fitter’ principle, but the maximum accuracy using a sample test and a neural network model is 69.9%, far from that obtained by classic bankruptcy prediction models in the case of mature companies.

The sample of companies founded in 2007 and the subsequent years analysed correspond to a period of economic crisis. To increase the validity of the results, the same analyses were conducted with another sample of companies created in 1999; this was a non-crisis period. The hypotheses were accepted and the prediction results are very close, which gives robustness to the conclusions of the study. These findings have remarkable practical implications, since analysts and investors would do well to analyse the accounting information of start-ups: if a newly created company already presents good values for the main financial indicators it is more likely to survive than those that present difficulties. This does not mean that analysts and investors should only focus on accounting information, however, since the models show that much remains unexplained.

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Category	Determinants	Positive influencing	Negative influencing	Not influencing
Firms peculiarities	Size	Mata (1994); Geroski (1995); Agarwal & Audretsch (2001); Geroski et al. (2010); Fotopoulos & Louri (2000); Delmar et al. (2013)	Laitinen (1992)	Audretsch et al. (1999)
	Age	Freeman et al. (1983); Geroski (1995); Geroski et al (2010); Delmar et al. (2013)		Rannikko et al. (2019)
Environmental factors	Macroeconomic conditions	Geroski et al. (2010)	Davidsson & Gordon (2016)	
	Industry dynamics and characteristics	Audretsch (1991); Mata & Portugal (1994); Geroski et al. (2010)		
	Incubation	Schwartz (2009); Schwartz (2013)		Mas-Verdú et al. (2015)
Organization Strategy	Innovation and new technology	Audretsch (1991); Audretsch (1995); Bayus & Agarwal (2007)	Hyytinen et al. (2015); Boyer & Blazy (2014)	
	Strategic actions: products, markets, business plan, organizational relationships	Brüderl et al. (1992); Stuart et al. (1999); Delmar & Shane (2003); Delmar & Shane (2004); Giarratana & Fosfuri (2007)		
Financial performance	Profitability	Laitinen (1992); Fotopoulos & Louri (2000); Wiklund et al. (2010); Delmar et al. (2013); Laitinen (2017).		Dosi et al. (2017)
Financial slack	Leverage	Cooper et al. (1994); Robb & Robinson (2014); Cole & Sokolyk (2018)	Laitinen (1992); Cressy (1996); Fotopoulos & Louri (2000); Wiklund et al. (2010); Huynh et al. (2010); Cole & Sokolyk (2018)	
	Liquidity	Wiklund et al. (2010); Lukason & Käsper (2017)		
Human capital	Entrepreneur previous experience, formation and abilities	Bates (1990); Cooper et al. (1994); Gimeno et al. (1997); Davidsson & Honig (2003); Bosma et al. (2004); Colombo & Grilli (2010); Cassar (2014)		Baum & Silverman (2004)
	Employees' talent	Acs et al. (2007); Geroski et al. (2010)		

Table 1. Studies on Success Factors of Start-ups' Survival.

NACE Rev. 2 codes	Description	Number of firms
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	3
26	Manufacture of computer, electronic and optical products.	44
50	Water transport.	21
51	Air transport.	4
58.2 to 63	Motion picture, video and television program production, sound recording and music publish activities; Programming and broadcasting activities; Telecommunications; computer programming, consultancy and related activities; Information service activities.	833
64 to 66	Financial and insurance activities.	489
69 to 75	Legal and accounting activities; Activities of head offices, management consultancy activities; Architectural and engineering activities, technical testing and analysis; Scientific research and development; Advertising and market research; Other professional, scientific and technical activities; Veterinary activities.	3,207
78	Employment activities.	57
80	Security and investigation activities.	54
84 to 93	Public administration and defence, compulsory social security; Education, Human health and social work activities; Arts, entertainment and recreation.	1,455

Table 2. The Sectors Analysed.

Source: Eurostat indicators on High-tech industry and Knowledge-intensive services (Eurostat, 2016).

Foundation year (t)	**t+2**	**t+3**	**t+4**	**t+5**	**t+6**	**t+7**	**t+8**
Total	6,167	5,802	5,298	4,975	4,641	4,240	3,985
Failed	364	504	323	334	401	255	264
Non-failed	5,803	5,298	4,975	4,641	4,240	3,985	3,721
Bankruptcy (%)	5.92%	8.69%	6.10%	6.71%	8.64%	6.01%	8.69%
Survival (% accumulated)	94.08%	85.39%	79.29%	72.58%	63.94%	57.93%	49.24%

Table 3. Percentage of Bankruptcy and Survivor Companies for Each Year (t=2007).

Variable	*Definition*
H1 Size	
TA	Total Assets
H2 Profitability	
ROA	Return on assets: Earnings Before Interest and Taxes/Total Assets
PROFIT	Dummy variable equals to 1 if the return on assets (ROA) is positive
H3 Debts	
TL/TA	Debt ratio: Total Liabilities /Total Assets
ICR	Interest coverage ratio: Earnings Before Interest and Taxes/Interest Expense
DCR	Debt coverage ratio: Earnings Before Interest and Taxes/Total Liabilities
CF/TL	Cash Flow/Total Liabilities
H4 Liquidity	
WC/TA	Working capital ratio: (Current assets - Current liabilities)/Total Assets
WC	Dummy variable equals to 1 if the working capital is positive
CR	Cash ratio: Cash/Current liability
H5 Employees	
R/E	Revenue per employee: Revenues /Number of Employees
C/E	Staff costs per employee: Personnel Expense /Number of Employees

Table 4. Variables Employed for the Hypotheses Testing and their Definition.

A) Continuous predictors	All (N=6,167)			Failed (N=364)			Non-failed (N=5,803)			MW test
	Median	Mean	St dev	Median	Mean	St dev	Median	Mean	St dev	(Z and sig.)
Total assets, TA	99.67	4,197	112,989	60.59	615	5,851	102.85	4,430	116,587	-6.782***
Return on assets, ROA	0.03	-0.20	3.35	-0.04	-0.81	4.30	0.04	-0.16	3.28	-8.517***
Debt ratio, TL/TA	0.88	1.02	3.01	0.97	1.31	2.19	0.88	1.00	3.05	-4.576***
Interest coverage ratio, ICR	3.51	-1,581	365,119	-3.99	2,339	56,050	3.79	-1,820	375,815	-7.541***
Debt coverage ratio, DCR	0.09	-37.39	2,889	-0.04	-0.30	3.11	0.10	-39.78	2,980	-8.530***
Cash Flow to liabilities, CF/TL	0.05	0.22	6.26	-0.03	-0.15	0.63	0.06	0.24	6.43	-5.907***
Working capital ratio, WC/TA	0.05	-0.15	2.14	-0.06	-0.61	3.52	0.06	-0.12	2.02	-4.508***
Cash ratio, CR	0.30	5.39	180.72	0.19	0.85	2.16	0.30	5.67	186.08	-3.878***
Revenue per employee, R/E	56.99	112.47	306.12	41.44	76.70	120.81	58.15	114.71	313.99	-5.893***
Costs per employee, C/E	22.51	29.58	33.52	19.06	28.98	36.84	22.66	29.62	33.30	-2.641***

B) Dummy predictors	All (N=6,167)			Failed (N=364)			Non-failed (N=5,803)			Chi test
	Median	Mean	St dev	Median	Mean	St dev	Median	Mean	St dev	(Chi and sig.)
PROFIT	1.00	0.62	0.49	0.00	0.44	0.50	1.00	0.63	0.48	54.83***
WC	1.00	0.58	0.49	0.00	0.46	0.50	1.00	0.59	0.49	23.03***

Table 5. Exploratory Analysis and Means Test.

Panel A) was made with the continuous variables and shows a Mann−Whitney U test.
Panel B) was made with the dummy variables and shows the results of a Pearson's chi-square test.

*** significant at 1% level.

Predictors	Cox Regression		
	Beta	p- value	Exp(B)
Total assets, TA	-0.104	0.000	0.901
Return on assets, ROA	-0.49	0.000	0.608
Debt ratio, TL/TA	0.838	0.000	2.311
Interest coverage ratio, ICR	-0.001	0.000	0.999
Debt coverage ratio, DCR	-0.268	0.000	0.765
Cash Flow to liabilities, CF/TL	-0.914	0.000	0.401
Working capital ratio, WC/TA	-0.356	0.000	0.700
Cash ratio, CR	-0.100	0.000	0.905
Revenue per employee, R/E	-0.129	0.000	0.879
Costs per employee, C/E	-0.148	0.000	0.863
PROFIT	0.485	0.000	1.625
WC	0.336	0.000	1.399

Table 6. Survival Analysis Results.

Application of Cox's regression to the start-ups survival, using financial indicators as explanatory variables (N=6,167).

		Train sample			Test sample			
	Beta and significance	Accuracy (%)	True negative rate (%)	True positive rate (%)	Accuracy (%)	True negative rate (%)	True positive rate (%)	AUC, area under ROC curve
Total assets, TA	0.244***	57.0%	63.7%	50.0%	52.7%	62.8%	52.3%	0.606
Return on assets, ROA	0.906***	62.0%	47.2%	71.1%	73.3%	46.4%	74.2%	0.633
Debt ratio, TL/TA	-1.661***	62.0%	46.5%	75.9%	68.9%	49.3%	69.5%	0.613
Interest coverage ratio, ICR	0.002***	63.2%	48.5%	77.9%	63.9%	53.8%	64.5%	0.643
Debt coverage ratio, DCR	0.521***	60.3%	70.8%	49.7%	49.6%	72.0%	48.9%	0.634
Cash Flow to liabilities, CF/TL	1.895***	63.8%	54.9%	71.8%	67.1%	53.4%	67.5%	0.646
Working capital ratio, WC/TA	0.713***	61.5%	52.2%	70.9%	65.1%	45.8%	65.8%	0.571
Cash ratio, CR	0.132**	57.5%	40.5%	73.1%	42.9%	70.8%	69.9%	0.565
Revenue per employee, R/E	0.406***	61.8%	59.6%	64.0%	56.5%	56.0%	56.6%	0.596
Costs per employee, C/E	0.249*	57.1%	51.7%	62.3%	59.2%	48.9%	59.5%	0.542
PROFIT	0.851***	60.3%	55.0%	65.7%	63.0%	57.4%	63.2%	0.597
WC	0.849***	60.3%	56.2%	64.6%	58.5%	52.0%	58.7%	0.565

Table 7. Univariate Logistic Regressions Analysis for Predicting Bankruptcy, Showing Beta Coefficients and Significance Levels.

Train sample comprises 364 firms, where 182 are failed firms and 182 are non-failed firms. Test sample comprises 5,803 firms, where 182 are failed firms and 5,621 are non-failed firms in the same period. True negative rate = 1 − Type 1 error rate; True positive rate = 1 −Type II error rate. AUC is the area under receiver operating characteristic (ROC) curve.

* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

		Model 1 (Logistic Regression)	Model 2 (MLP Neural Network)	Model 3 (RBF Neural Network)	Model 4 (CHAID Decision Tree)
Train sample	Accuracy (%)	65.9%	64.3%	64.3%	66.8%
	True negative rate (%)	65.4%	56.6%	63.2%	61.5%
	True positive rate (%)	66.5%	72.0%	65.4%	72.0%
Test sample	Accuracy (%)	62.6%	69.9%	64.6%	65.3%
	True negative rate (%)	62.3%	53.6%	61.2%	57.9%
	True positive rate (%)	62.6%	70.4%	64.7%	65.6%
	Area under ROC curve (AUC)	0.660	0.662	0.668	0.630

Table 8. Multivariate Logistic Regression (LR), Multilayer Perceptron (MLP), Radial Basis Function (RBF) and CHAID Decision Tree Results.

Train sample comprises 364 firms, where 182 are failed firms and 182 are non-failed firms. Test sample comprises 5,803 firms, where 182 are failed firms and 5,621 are non-failed firms in the same period. True negative rate = 1 − Type 1 error rate; True positive rate = 1 − Type II error rate.

A) Continuous predictors	All (N=2,600)			Failed (N=150)			Non-failed (N=2,450)			MW test (Z and sig.)
	Median	Mean	St dev	Median	Mean	St dev	Median	Mean	St dev	
Total assets, TA	122.18	9,134.05	272,167	87.53	1,733	12,211	125.78	9,590	280,412	-3.198***
Return on assets, ROA	0.02	-0.06	0.73	-0.05	-0.46	1.15	0.03	-0.04	0.68	-6.221***
Debt ratio, TL/TA	0.85	0.88	0.94	0.95	1.25	1.27	0.84	0.86	0.92	-5.200***
Interest coverage ratio, ICR	3.74	11,167	325,545	-0.23	43.75	1,718	4.00	11,857	335,470	-5.314***
Debt coverage ratio, DCR	0.08	0.17	3.35	0.00	-0.22	1.78	0.08	0.19	3.43	-6.121***
Cash Flow to liabilities, CF/TL	0.06	0.33	4.87	-0.01	-0.24	1.65	0.07	0.37	5.00	-6.378***
Working capital ratio, WC/TA	0.00	-0.11	0.94	-0.15	-0.47	1.36	0.00	-0.09	0.91	-4.251***
Cash ratio, CR	0.20	5.29	145.59	0.09	0.97	4.33	0.21	5.56	149.96	-1.445***
Revenue per employee, R/E	46.79	171.47	3,306.08	36.74	135.74	481.52	47.66	173.67	3,404.42	-3.080***
Costs per employee, C/E	15.90	23.50	58.67	15.82	20.15	60.32	16.44	23.70	16.06	-0.453

B) Dummy predictors	All (N=2,600)			Failed (N=150)			Non-failed (N=2,450)			Chi test (Chi and sig.)
	Median	Mean	St dev	Median	Mean	St dev	Median	Mean	St dev	
PROFIT	1.00	0.59	0.49	0.00	0.42	0.49	1.00	0.60	0.49	19.50***
WC	1.00	0.50	0.50	0.00	0.36	0.48	1.00	0.51	0.50	13.14***

Annex 1a. Validation, Using a Different Sample of Companies Created in 1999. Exploratory Analysis and Means Test.

Panel A) was made with the continuous variables and shows a Mann−Whitney U test.
Panel B) was made with the dummy variables and shows the results of a Pearson's chi-square test.

*** significant at 1% level.

Predictors	Cox Regression		
	Beta	p- value	Exp(B)
Total assets, TA	-0.115	0.000	0.891
Return on assets, ROA	-0.720	0.000	0.487
Debt ratio, TL/TA	0.619	0.000	1.857
Interest coverage ratio, ICR	-0.066	0.000	0.936
Debt coverage ratio, DCR	-0.136	0.000	0.873
Cash Flow to liabilities, CF/TL	-0.113	0.000	0.893
Working capital ratio, WC/TA	-0.473	0.000	0.623
Cash ratio, CR	-0.102	0.000	0.903
Revenue per employee, R/E	-0.123	0.000	0.885
Costs per employee, C/E	-0.103	0.000	0.902
PROFIT	0.418	0.000	1.518
WC	0.324	0.000	1.382

Annex 1b. Validation, Using a Different Sample of Companies Created in 1999. Survival Analysis Results.

Application of Cox's regression to the start-ups survival, using financial indicators as explanatory variables (N=2,600).

	Beta and significance	Train sample Accuracy (%)	True negative rate (%)	True positive rate (%)	Test sample Accuracy (%)	True negative rate (%)	True positive rate (%)	AUC, area under ROC curve
Total assets, TA	0.160***	50.7%	46.7%	54.7%	50.7%	49.6%	66.2%	0.530
Return on assets, ROA	1.257***	60.7%	45.3%	76.0%	81.1%	42.9%	82.4%	0.623
Debt ratio, TL/TA	-0.930**	60.7%	53.3%	68.0%	66.9%	53.2%	67.3%	0.607
Interest coverage ratio, ICR	0.056***	54.0%	54.8%	53.1%	69.1%	47.8%	69.8%	0.611
Debt coverage ratio, DCR	0.292***	57.3%	61.3%	53.3%	59.5%	59.2%	59.5%	0.613
Cash Flow to liabilities, CF/TL	0.239***	56.7%	54.7%	58.7%	66.0%	59.2%	66.3%	0.625
Working capital ratio, WC/TA	0.801***	56.7%	42.7%	70.7%	70.9%	48.1%	71.6%	0.575
Cash ratio, CR	0.166***	59.5%	41.3%	76.5%	71.3%	45.6%	72.1%	0.593
Revenue per employee, R/E	0.209***	49.7%	77.3%	20.8%	26.3%	83.1%	24.4%	0.573
Costs per employee, C/E	0.086	66.0%	54.7%	77.3%	52.4%	40.3%	52.8%	0.500
PROFIT	0.771***	57.0%	58.1%	56.0%	59.8%	60.5%	59.8%	0.571
WC	0.635***	57.3%	61.3%	53.3%	51.4%	67.5%	50.9%	0.573

Annex 1c. Validation, Using a Different Sample of Companies Created in 1999. Univariate Logistic Regressions Analysis for Predicting Bankruptcy, Showing Beta Coefficients and Significance Levels.

Train sample comprises 150 firms, where 75 are failed firms and 75 are non-failed firms. Test sample comprises 2,450 firms, where 75 are failed firms and 2,375 are non-failed firms in the same period. True negative rate = 1 − Type 1 error rate; True positive rate = 1 −Type II error rate. AUC is the area under receiver operating characteristic (ROC) curve.

* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

		Model 1 (Logistic Regression)	Model 2 (MLP Neural Network)	Model 3 (RBF Neural Network)	Model 4 (CHAID Decision Tree)
Train sample	Accuracy (%)	63.1%	63.3%	63.1%	63.1%
	True negative rate (%)	65.3%	68.0%	66.7%	65.3%
	True positive rate (%)	60.8%	63.3%	59.5%	60.8%
Test sample	Accuracy (%)	69.0%	72.1%	71.7%	69.2%
	True negative rate (%)	69.4%	72.6%	72.1%	69.6%
	True positive rate (%)	57.3%	72.1%	60.0%	58.7%
	Area under ROC curve (AUC)	0.694	0.696	0.694	0.692

Annex 1d. Validation, Using a Different Sample of Companies Created in 1999. Multivariate Logistic Regression (LR), Multilayer Perceptron (MLP), Radial Basis Function (RBF) and CHAID Decision Tree Results.

Train sample comprises 150 firms, where 75 are failed firms and 75 are non-failed firms. Test sample comprises 2,450 firms, where 75 are failed firms and 2,375 are non-failed firms in the same period. True negative rate = 1 − Type 1 error rate; True positive rate = 1 −Type II error rate. AUC is the area under receiver operating characteristic (ROC) curve.