The Determinants of Credit Default on Start-Up Firms.
Econometric Modelling using Financial Capital, Human Capital and Industry Dynamics Variables

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Abstract:

In this paper we investigate the behaviour of credit default in start-up companies. Using a logit regression technique on a panel data of 1430 start-ups and considering a tracking period of three years, we tested the impact on the probability of occurrence of the first credit event in financing agreements due to variables grouped into three categories: financial capital, human capital and industry dynamics. We concluded from a financial point of view, that the support provided by partners in the financing of the company’s activity, the intensity of use of assets under management and reduced debt pay-back periods, were decisive in mitigating risk of default. In addition we found that the occurrence of a credit event will only be as limited as higher the quality of human capital held by the promoter of the project in terms of educational background and management experience.

Keywords: Credit Default; Start-Up; Financial Capital; Human Capital; Industry Dynamics
1. Introduction

Start-up companies are part of bank’s and other financial operator’s loan portfolios and to that extent they are subject to their credit risk monitoring processes. The Basel II Capital Accord was decisive in strengthen in credit risk evaluating and managing systems and among them assign a relevant dimension to the internal rating models and to the topic of credit default. Start-ups are firms in an early stage of their life cycle, strongly marked, as widely recognized in the literature, for very high heterogeneity. It is therefore to be expected that her credit default behaviour will be different from firm segments with other life maturities.

New companies attracted the attention of the economy from an early stage. Since Adam Smith economists have expected that the entry of new competitors into the market contributes decisively in driving prices to an optimum level by promoting the efficient allocation of production factors. The role of entrepreneurship has been present in economic theory since the works of Richard Cantillon and Jean-Baptiste Say in the eighteenth and nineteenth centuries as pointed out by Santarelli et al. (2007). However, it is in the beginning of the twentieth century that Schumpeter in his Theory of Economic Development lays the foundations for a revolution in economic theory demonstrating that entrepreneurship is the force that motorizes economic development. The most innovative idea is that new companies force the exit from the market of inefficient firms in a process of what he called "creative destruction" and is a crucial determinant of economic growth. According to Mata et al. (1996), since the work of Schumpeter that new companies bear a significant responsibility for new products and process that are continuously introduced into the market and in this way they play a key role in advancing technology and economic growth. Santarelli et al. (2007), refer to the fact that in recent years the role of start-up companies has been consistently proposed as an additional factor in explaining economic growth in developed countries. The same conclusion is driven in the 2010 Report of the Global Entrepreneurship Monitor, according to which the role of start-ups in the assessment of economic growth and competitiveness has been neglected, not because it has been considered irrelevant, but due to lack of quantitative information on this sector.
The literature on start-ups is quite extensive and the findings are quite controversial, however Geroski (1991) set some standards which he highlighted as stylized facts that are widely referred to in the literature. Firstly, an impressive number of start-up companies are born every year in the economy; secondly, although numerous, the start-up companies are typically small; thirdly, only a small percentage of start-up companies survive the first year; fourthly, the relationship between the size of the firm and company’s future growth is also true for start-ups.

As mentioned, these types of companies that are still in an early stage of their life cycle are also part of bank loan portfolios and are therefore subject to their credit risk evaluation and management processes although in different patterns than the segment of firms with different maturity. Indeed, the importance that the internal rating models have begun to assume to financial operators since the 90s of last century in credit risk management and evaluation (in approval, monitoring, pricing and provisioning), have acquired with the Basel II Capital Accord a mandatory character. The internal rating models have assumed an even more increased importance to banks than that the external ratings (Rating Agencies) represent for the operators in the capital markets, in the definition of risk-profitability adjustment and in the definition of investment strategies. One of the most important objectives of Basel II was precisely to improve the efficiency of banks and other financial operators risk management. The new Basel Capital Accord has imposed a new impetus to the research, development and deepening of predictive models of default.

Since the seminal works of Beaver (1967) and Altman (1968) studies about default prediction methodologies have multiplied in the literature. These studies have focused mainly on the approach of large companies listed on the capital markets and elect as statistical models inputs almost exclusively financial facts, i.e., a pool of financial indicators (usually related to liquidity, profitability, leverage, coverage and activity), obtained from historical accounting information. More recently, studies on this issue

1 There are other methodologies for assessing credit risk based on different analytical processes, for example: artificial intelligence models, models based on market interest rate spread, models based on death rates and credit migration; options models
are especially oriented to default of small and medium sized enterprises, Altman et al. (2005) Altman et al. (2007) and to the importance that the introduction of qualitative variables in the models (soft facts), in addition to the traditionally used quantitative variables (hard facts), takes on improving the predictive performance of default models, Grunert et al. (2002), Lehmann, B. (2003), Altman et al. (2008).

The important role played by small and medium sized enterprises is recognized in most developed economies among other reasons, because of their relative weight in overall companies and their contribution to employment, but also because of the high financial resources volume that is allocated to the development of their businesses. The recognition of this specific business segment is made by Basel II, which differentiates them from larger companies as regards the calculation of minimum capital requirements of its credit operations. Recent studies recognize that the adoption of default prediction models specific to small and medium sized companies, i.e. distinct from those adopted for large companies, significantly enhance their predictive ability, Altman et al. (2007) and Altman et al. (2008). For this reason, in their credit risk management, banks tend to adopt different methodologies for determining the default in these two business segments, according to Altman et al. (2007) with benefits to their profitability and to minimize the expected and unexpected loss with the reduction of almost 0.5% in capital allocated to this portfolio of companies (considering Internal Rating Approach of Basel II).

Some recent works, Grunert et al. (2002), Lehmann, B. (2003) and Altman et al. (2008) conclude that the inclusion of qualitative variables (soft facts or non financial factors) in the risk evaluation models of small and medium enterprises in addition to the historically used quantitative variables (hard facts or financial factors) improve the statistical accuracy of those models.

As highlighted by Lehmann, B. (2003), start-up companies tend to be segregated in the banks’ risk management methodologies. Banks adopt specific management and evaluation risk models for start-ups that don’t make extensive use of accounting information, and that are especially based on soft facts (non financial factors). Soft facts
are risk factors which, by their nature, are not verifiable, and are dependent on the environment in which they are primarily produced and are manipulated by those who produce them. Once the credit decision is taken in an environment of asymmetric information, the intensive use of soft facts in decision-making, highlights the agency dilemma problems present in banks’ organizational structure and increase adverse selection risk.

Considering as is exhaustively recognized by the literature, the role that the first years after the start up pose to the future of firms, Cressy (2006), Bartelsman E. et al. (2005), Audrech et al. (1999), Geroski (1995), this paper aims to investigate the behaviour of credit default in start-up companies. Under the high heterogeneity that characterizes this segment of companies, Santarelli et al. (2007), we intend to test the impact on credit default of variables grouped into three categories: financial capital, human capital and industrial dynamics.

The rest of this paper is organized as follows. In Section 2 we show the relevant literature on the issues addressed here. It is organized into three sub-sections: the first subsection addresses recent studies on forecasts of default, their recent guidance for small and medium sized enterprises and the increasing weight of soft facts in the default models risk factors; the second subsection, refers to the role of Human Capital in the performance of start-ups: General Human Capital and Specific Human Capital, and finally in the third subsection, we analyse the effect of industry environmental conditions in the performance of start-ups. Section 3 presents the statistical framework: the dependent variable definition; the theoretical justification for the tracking period considered and the enunciation of the explanatory variables potentially candidates for inclusion in the estimated models, considered as theory and literature premises examined in the previous section, with an indication of the estimate coefficients signals. The methodology and databases used will also be addressed. The estimation results are examined in Section 4, ending in Section 5 with the final remarks.
2. Review of Literature

2.1. Recent studies on default prediction. The guidance for small and medium sized enterprises and the increasing weight of soft facts as risk factors in default prediction models.

The studies of Beaver (1967) and Altman (1968) were pioneers in investigating the default risk. In the last 45 years studies on this subject have been multiplied. The Basel II Capital Accord, with its goal of improving financial operators risk management efficiency, made a decisive contribution by stressing the importance of internal rating models and credit default.

Recognizing the economic relevance of small and medium sized enterprises and the importance and differentiation that Basel II Capital Accord provides to them, Altman et al. (2007) develop a default prediction model specifically adapted to this firms. These authors investigate whether the application of a model constructed from a sample of large companies when applied to the prediction of default for small and medium size enterprises, guarantees the same level of default prediction accuracy as a model built specifically to data from small and medium size enterprises. Considering a panel data of 2010 small and medium sized American companies for the period between 1994 and 2002 (including 120 defaulters) and taking into consideration the concepts of small and medium sized companies and probability of default (PD) defined in Basel II, the authors use logit regression technique to design a default prediction model specifically for small and medium sized enterprises. Consistently with literature, the authors define five categories of financial ratios obtained from historical accounting data, which combined are able to identify a company financial profile (relating to liquidity, profitability, leverage, coverage and activity). From an extensive pool of 22 financial ratios, they select one from each category with the highest default event predictive accuracy. The model achieved has high prediction accuracy, both in absolute terms and also when compared with the generic model for large companies - Z-Score, revealing a degree of accuracy almost 30% higher.
The authors also conclude that the banks’ adoption of prediction models specific to small and medium sized enterprises allows, on the one hand, the optimization of the profitability of this business segment and on the other hand, reduces by about 0.5% the capital requirements assigned to this portfolio of companies (using the Internal Rating Basis Approach under the first pillar of Basel II) than applying a generic corporate model. As other authors they conclude therefore that small and medium size companies risk behaviour is different from large companies and that the discriminating power of a model to apply to small and medium sized enterprises built from a sample of small and medium sized companies is superior to a generic corporate model.

The conclusion of this study is reaffirmed by the study of Altman et al. (2008), but this time based on a significantly bigger sample and related to another geographical area. From a sample of nearly six million small and medium sized enterprises in United Kingdom for the recent economic period between 2000 and 2007, the authors confirm the strength of a default prediction model built specifically for small and medium sized enterprises. They test precisely the same financial ratios related to liquidity, profitability, leverage, coverage and activity that revealed high capacity to evaluate default for the United States economy in 2007. At the same time, they explore the value added which results from the introduction of qualitative nature independent variables in the models such as, the existence of county court judgements; the existence of audited accounts; the existence of cash flow statements; audit report judgement; age of the form; economic sector. They conclude that their presence in the model in addition to the financial variables, contributes to increase precision in the order of 13%

The credit relationship sets a paradigmatic example of information asymmetry in face of credit borrower low transparency, which can lead to problems of adverse selection for banks. Thus the information is a critical input to banking industry risk management. Haken (2004) characterizes the banks as experts in information management and risk monitoring. To overcome the issues of information asymmetry generated in credit relationship, banks use two types of information: hard information (financial facts) and soft information (non financial facts). In an exhaustive research on the definition and distinction between these two risk factors, Peterson (2004) classifies the soft
information as qualitative in its nature; "forward looking"; personal and dependent on the context in which it is produced and treated. Subjective judgments, opinions and perceptions are absent of hard information, which is quantitative in its nature; "backward looking"; impersonal and independent of the context in which it is produced.

A recent attempt to explore the importance of non financial factors in rating models was carried out by Grunert et al. (2002). From a sample of 160 firms obtained from the databases of the four largest commercial banks in Germany between 1992 and 1996 and using Probit analysis, the authors conclude that the combined use of financial and non financial factors (quality management and market position) contributes to a more precise explanation of the probability of default than the exclusive use of financial factors. This conclusion is consistent with banking practice as stated by Gunther et al. (2000) exhaustive survey: 70 of the 145 German banks inquired confirm that their risk management methodologies rely heavily on qualitative factors. The authors can not determine the net benefits to financial operators related to the introduction of qualitative risk factors, considering that the costs of obtaining qualitative information were not calculated. According to Petersen (2004), qualitative information is expensive due to the difficulty of collecting, stockage, the complexity of transmission; it is more difficult to treat in an automated manner and does not allow economies of scale associated with a technologically standardized treatment.

For Lehmann, B. (2003), the subjective judgments of analysts, market position, management quality and historical relationship with the bank, are soft facts susceptible to improve the rating models predictive ability, positively complementing the hard facts based on financial ratios. Like the previous study, this too is inconclusive as to whether the predictive model performance improvement resulting from the introduction of soft facts is able to offset the cost of obtaining it. Lehmann B. (2003) used a sample of 20,000 small and medium sized companies from all industries integrated in a German commercial bank’s client portfolio. The default probability is carried out through a logistic regression and the adopted methodology is the comparison of two models: one including and one excluding qualitative factors. The author concludes that the model
including qualitative variables as greater accuracy and also concludes that the hard facts work better in higher risk areas than the soft facts.

Soft facts contribute positively to the estimation of the quality of the debtor, in this way reducing the allocation of capital to cover the Value at Risk assets. But soft facts are not verifiable and are dependent on the environment in which they are produced, as they are manipulated by those who produce them it creates a moral hazard problem arising from that agency dilemma, which to be avoided, requires changes in banks organizational structure, as concluded Godbillon et al. (2006).

2.2. The Role of Human Capital in the performance of start-ups. General Human Capital and Specific Human Capital.

The literature acknowledges the high heterogeneity that characterized start-ups’ founders: work experience, family tradition, financial condition, age, gender, education, motivation, capacity to innovate and psychological attitudes such as risk aversion, as indicated Santarelli et al. (2007). The start-ups’ founders are in his words "a rather heterogeneous aggregate where innovative entrepreneurs are to be found together with passive followers over-optimist gamblers and even escapees from unemployment " many of them likely to make mistakes that condemn start-ups to an early failure, contributing to market turbulence and not for the technological and economic growth, that Schumpeter in the early twentieth century, innovatively appointed as "creative destruction".

Colombo et al. (2005), considering a sample of 391 Italian technology-based start-ups, concluded that founders with high levels of human capital, access to private equity funding to begin operations on a larger scale (and therefore have a greater probability of success) than individuals with the same back-ground but that rely solely on funding based on their assets and bank debt. The type of funding is irrelevant to start-ups initiated by founders with low levels of human capital. Based on a sample of 2000 start-ups that opened account in 1988 in a United Kingdom bank and considering a number of variables related to human capital and financial capital, Cressy (1996) shows that
human capital is the real determinant of survival of start-ups and that the correlation between financial capital and the success of start-ups is spurious.

Brüderl et al. (1992), show that education and human capital play an important role in increasing the survival probability of start-ups and improve their post-entry performance. Human capital promotes founders’ productivity which determines higher profitability and greater chance of survival. They propose a theoretical framework that distinguishes two forms of human capital of the company’s founder. General human capital, related to the level of education, and specific human capital, which considers the management experience and industry specific experience. That is, while the general human capital corresponds to a set of skills and knowledge that are useful in different businesses and that are transferable to different situations, the specific human capital, by contrast, includes skills and knowledge less transferable and useful in the context where they are generated, Baptista et al. (2009).

With regards to general human capital, Baptista et al. (2007) point to the fact that the founders schooling contributes to a greater markets and technology learning capacity; provide a greater predisposition to detect opportunities in the environment and develop learning attitudes and organizational skills. Baptista et al. (2009) state that education is related to knowledge, skills, problem solving, ability, discipline, motivation and self-confidence.

In an extensive review of several studies on whether and to what extent the founders’ schooling impacts on their pre-entry selection and post-entry performance in developed countries, Sluis et al. (2005), conclude that there is a significant and positive relationship between education level and number of years of schooling, with the future performance of the founder. According to these authors, the greater the level of education and more years of schooling, the greater the likelihood of better performance with respect to survival and post-entry growth. Santarelli et al. (2007) point out that the specific skills associated with education in economics and management and education in technical and scientific fields, are better indicators of post-entry performance, particularly with regard to technology based start-ups.
As far as specific human capital is concerned, Baptista et al. (2007) reported that professional experience and management experience (whether in the same industry), positions the founder better to detect opportunities and raising funding for the start-up, also contributing to the development of skills for the organization of the new business. When these experiences occur in the same industry of the start-up company, the founders acquire industry-specific human and social capital, i.e., technological and market specific knowledge plus professional and social networking contacts that contribute positively to the acquisition and management of technical and human resources. According to Santarelli et al. (2007), the start-up founder is strongly influenced by his background, particularly for his previous work experience. They add that the specific education and business and management experience are shown to be correlated with a post-entry performance above the average.

In recent work, based on a very large sample for the Portuguese economy for the period between 1986 and 2005, Baptista et al. (2009) conclude that start-up founders with more education are more likely to succeed. The results also point to the fact that start-ups whose founders have management experience in the same sector, show a greater likelihood of survival and better performance in terms of sales.

2.3. Industry environmental conditions at entrance effect in the performance of start-ups.

Studies conducted for an extensive variety of countries and industries in the last two decades suggest four main industry-level variables that may influence a start-up firm’s survival: industry growth, industry entry rate/barriers to entry, market concentration and economies of scale.

Indeed the economies of scale are a barrier to entry for the reason that in industries where the minimum efficient scale is high, companies need to have a larger market share to be efficient and businesses operating below the minimum efficient scale have cost disadvantages in relation to more efficient firms. According to Audrecht (1995), one of the reasons for the early failure of many start-up companies, stems precisely
from their size at the entrance to be under the minimum efficient scale so that they are impaired by a cost disadvantage compared to more efficient companies in the market. For this reason in many industries start-ups originate just what was called, in early 80s of the last century "turbulence", as pointed out by Santarelli et al. (2007)

Industries that have high growth rates (typically related to early stages of their life cycle), provide a market environment in which the probability of exit is reduced. The profitability of growth industries is higher than in other similar industries with different trends and this fact makes the survival of new entrants easier, R. Schmalensee (1989). Mata and Portugal (1994) find a positive and significant effect between industry growth and a start-up company's survival. Baptista, et al. (2007) point to the fact that companies that enter growing markets are predictably subject to less competitive pressure and so it would be expected to have a higher probability of survival.

One of the elements of market competitive structure is the size of the entry. There is consensus in the literature that markets with high entry rates are those with the highest exit levels. The theoretical and empirical arguments for this purpose are of two orders: on the one hand, a high entry rate points to a low degree of protection in the market for what might be expected to be also a high exit rate, on the other hand, barriers to entry are also exit barriers, as the extent and irreversibility of investments that deter entry also constitute an obstacle to exit. Geroski (1995) notes that obstacles to entry are actually more barriers to mobility than barriers to entry. Mata and Portugal (1994) note the existence of a strong positive correlation between entry and exit due in large scale, to premature exit in industries characterized by very high entry. It will therefore to be expected that start-ups entering into industries with high entry rates have a lower probability of survival, as indicated by Baptista et al. (2007).

The effect of market concentration level on a firm’s survival perspectives suffers from consistent theoretical propositions and conclusive empirical evidence. However, Mata and Portugal (1994), in a study for the Portuguese economy, consider the relationship between the industry concentration level and a firm’s survival to be inconclusive.
From a theoretical perspective, the relationship between market concentration and survival is assessed in two orientations. On the one hand, competition is the force that contributes to mortality. The competition increases with the number of players in the market enhancing the level of mortality. There is consensus for the theory that competitive markets (ie, faraway from the monopoly extreme and closer to perfect competition) trigger a strong disciplinary power and lead inefficient companies out of the market. Another theoretical orientation emphasizes the fact that the market concentration facilitates collusion so in highly concentrated markets incumbents exercise a retaliation power against start-ups.

Within the framework of theoretical and empirical inconsistencies Baptista et al’s. (2007) approach was followed, considering the market concentration as a proxy for the impact of the intensity of competition in the survival of start-ups.

3. Methodology and Data

In this Section the statistical framework of the text is carried out: it starts with the exposure of the variables that integrate the estimated models and concludes with the presentation of the used sample.

3.1. Definitions of variables and Methodology

This subsection begins with the explanation of default concept and the justification for the tracking period used, subsequently; the several explanatory variables included in estimated models with the expectations of signs to their regression coefficients will be presented.

On the back of Lehmann, B. (2003), the concept of default considered here corresponds to the first internal credit event (credit responsibility overdue for more than 90 days), which determines the communication to Bank of Portugal Credit Responsibilities Central the this type of loans in default2 and therefore the establishment of loan loss

2 According to Instrução 16/2001 do Banco de Portugal
provision, which occurred during the three years after companies start-up. It does not mean that the start-up credit borrower has definitely defaulted in the financing agreement, i.e. not necessarily having stopped all payments, still makes the timely fulfillment of contractual obligations less likely. It is one of the criteria of default mentioned in Basel II and a trigger for the enhancement of credit loan impairment.

Lehmann, B. (2003) argues that the true predictive power of the model is demonstrated by its ability to detect the first default and not by extrapolation of past failure. According to him, financial institutions are especially interested in the potential surprises of their credit portfolios of non defaulters rather than in credit agreements of defaulters, framed, by this feature, in specific processes of monitoring and risk management.

The definition of default used is crucial for the results obtained, therefore studies based on different concepts of default are not likely to be easily compared. The guidelines followed in this text are identical to that of Lehmann, B. (2003) and Grunert et al. (2002), but divergent, for example from Altman et al. (2008), whose work in assessing the impact of the introduction of soft facts into predictive models built specifically for small and medium-sized U.K. companies used as default concept small business firms that entered into voluntary liquidation, administration or receivership. In the study related to modeling credit risk for small and medium-sized firms in the U.S. economy, Altman et al. (2007), considered as defaulters companies that went bankrupt under Chapter 11 of the U.S. Bankruptcy Code. In the seminal studies on this theme, the concepts of a default were not identical: Beaver (1966) considered default as the inability for a company to settle the financial obligations at maturity; Altman (1968) considered as defaulters firms that are legally bankrupt and either are in liquidation or under supervision of the courts in a reorganization process.

Thus, the explanatory variable default is a binary qualitative variable, which identifies the first internal credit event connected with a financing contract occurred during the three years after the firm’s constitution. It assumes the value 1 in case of a company’
default and 0 if the event has not occurred during the three years after start-up (non-default).

The adoption of three years as a timeframe for the default tracking is related to the concept of start-up itself and with the criticality to the company's future attributed by the literature to the first years after the start-up, as indicated by Cressy (2006) and Baptista, et al. (2007). Indeed, the literature on entrepreneurship shows the first three years after start-up as critical for the survival of new firms. The Global Entrepreneurship Monitor, which investigates entrepreneurship worldwide, defines start-ups as companies that have been in business for three and a half years or less. Bartelsman et al. (2005), conclude as a common feature to the ten OECD countries that focused on his research, which in most sectors, each year about 20% of firms enter and exit the market, between 20 and 40% of companies entering the market are unsuccessful in the first two years of life, and only between 40 and 50% of businesses survive beyond the seventh year. In a previous study Audrecht et al. (1999), the evolution of 1570 Italian industrial start-ups was tracked for a 6 year period and they concluded that the mortality rate tends to decrease but is heavily concentrated in the first two years of existence. In the same guideline Geroski (1995), indicates that the mechanism of displacement, which is the most striking feature of market entry, most severely affects young companies. Indeed, one of the stylized facts thoroughly standardized by the author and highly cited in the literature on this subject, points out as characteristic of market dynamics precisely the fact that only a small fraction of start-up companies survive the early years.

The explanatory variables used are organized into three groups according to assumptions of the theory and literature considered in Section 2. First, the explanatory variables of financial nature are presented, and then the explanatory variables related to human capital concluding with the identification of variables related to industrial dynamics.

The literature shows consensus on the high number of financial ratios that could contribute to the default explanation. Consistent with the literature examined in Section
In particular following the extensive work of Altman, Lehmann, B. (2003) and Grunert et al. (2002) on this issue, we tested various accounting ratios under the categories commonly used to characterize the company’s financial profile. The pool of 18 financial indicators potentially able to integrate the estimated models related to financial structure/leverage, liquidity, profitability, debt coverage/pay-back, and activity, together with their definitions, are presented in Table I.

With the exception of Debt Pay-back Period and Debt to Equity ratios, negative signs for the estimation coefficients of the other financial indicators should be expected.

### Table I

**Financial Capital Variables Definitions**

<table>
<thead>
<tr>
<th>Category</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leverage</td>
<td>Solvability Ratio: Equity / Total Liabilities</td>
</tr>
<tr>
<td></td>
<td>Financial Autonomy Ratio: Equity / Total Assets</td>
</tr>
<tr>
<td></td>
<td>Debt-to-Equity: Total Liabilities / Equity</td>
</tr>
<tr>
<td>Liquidity</td>
<td>Current ratio (Working Capital Ratio): Current Assets / Current Liabilities</td>
</tr>
<tr>
<td>Profitability</td>
<td>Basic Earnings Power Ratio: Ebit / Total Assets</td>
</tr>
<tr>
<td></td>
<td>Ebitda to Total Assets Ratio: Ebitda / Total Assets</td>
</tr>
<tr>
<td></td>
<td>Operating Profit Margin (Return on Sales Ratio): Ebit / Net Sales</td>
</tr>
<tr>
<td></td>
<td>Return on Assets Ratio: Net Profit / Total Assets</td>
</tr>
<tr>
<td></td>
<td>Return on Equity Ratio: Net Profit / Equity</td>
</tr>
<tr>
<td></td>
<td>Profit Margin (Net Profit Margin Ratio): Net Profit / Net Sales</td>
</tr>
<tr>
<td></td>
<td>Cash-Flow to Total Assets Ratio: Cash-Flow / Total Assets</td>
</tr>
<tr>
<td></td>
<td>Cash-Flow to Net Sales Ratio: Cash-Flow / Net Sales</td>
</tr>
<tr>
<td>Coverage</td>
<td>Debt to Ebitda Ratio: Net Debt/Ebitda</td>
</tr>
<tr>
<td></td>
<td>Debt to Cash-flow Ratio: Net Debt/Cash-flow</td>
</tr>
<tr>
<td></td>
<td>Interest Coverage Ratio (Times Interest Earned): Ebit / Interest Expense</td>
</tr>
<tr>
<td></td>
<td>Ebitda-to-Interest Coverage Ratio: Ebitda / Interest Expense</td>
</tr>
<tr>
<td></td>
<td>Retained Earnings to Total Assets Ratio: Retained Earnings / Total Assets</td>
</tr>
<tr>
<td>Activity</td>
<td>Asset Turnover Ratio: Net Sales / Total Assets</td>
</tr>
</tbody>
</table>
With regard to Human Capital the theoretical design defined by Brüderl et al. (1992) was followed, which distinguishes two forms of human capital of the company founder. Table II presents five variables related to human capital that could potentially integrate the estimated models: the first variable refers to General Human Capital and the remaining four to Specific Human Capital.

Table II
Human Capital Variables Definitions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Schooling</td>
<td>it is an ordinal qualitative variable related to education level of the founder at start-up, with the following definition:</td>
</tr>
<tr>
<td></td>
<td>0 if has no schooling</td>
</tr>
<tr>
<td></td>
<td>1 if has basic education</td>
</tr>
<tr>
<td></td>
<td>2 if has secondary education</td>
</tr>
<tr>
<td></td>
<td>3 if has a 3 year Bachelor degree</td>
</tr>
<tr>
<td></td>
<td>4 if has a 5 year Bachelor degree</td>
</tr>
<tr>
<td></td>
<td>5 if has a post-bachelor degree</td>
</tr>
<tr>
<td></td>
<td>6 if has a post-graduation degree</td>
</tr>
<tr>
<td></td>
<td>7 if has a Master degree</td>
</tr>
<tr>
<td></td>
<td>8 if has an MBA</td>
</tr>
<tr>
<td></td>
<td>9 if has a Doctor degree</td>
</tr>
<tr>
<td>Industry Experience</td>
<td>number of years of experience of the start-up company founder in the same industry</td>
</tr>
<tr>
<td>Management Experience</td>
<td>number of years of management experience of the start-up company founder regardless of taking place in the same industry or not</td>
</tr>
<tr>
<td>Success on Previous Projects</td>
<td>it is a binary qualitative variable related to the degree of success of the start-up company founder on previous projects supported by the Bank; it has the value 1 if there were previous successful projects and 0 otherwise</td>
</tr>
<tr>
<td>Business Plan:</td>
<td>it is a binary qualitative variable designed to capture the quality/sophistication of the start-up project, which has the value 1 if there is business plan at start-up and the value 0 otherwise</td>
</tr>
</tbody>
</table>

Negative signs are expected to estimate coefficients for both human capital explanatory variables: General Human Capital and Specific Human Capital.
Major Industry-level variables that could potentially influence the start-up’s default were built as shown in Table III, in a similar way as Baptista, et al. (2007).

**Table III**

*Industry-Level Variables Definitions*

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industry Growth</td>
<td>(Start-up company industry value added at the start-up year / Start-up company industry value added at the start-up previous year) - 1</td>
</tr>
<tr>
<td>Entry Rate</td>
<td>Number of companies born in the start-up industry at the start-up year / Number of existing companies in the start-up industry at the start-up year</td>
</tr>
<tr>
<td>Industry Concentration</td>
<td>Herfindahl-Hirschman (HHI) concentration index for the start-up company industry measured by the Net Sales of that industry at the start-up year</td>
</tr>
</tbody>
</table>

We can expect negative signs for estimating coefficients of explanatory variables related to the rate of industry growth and market concentration and a positive coefficient on the variable related to industry entry rate.

The explanatory variables related to Human Capital and Industry-level referred to above, include within them attributes in management quality and market positioning which are non financial factors that contribute positively, as has been seen in Lehmann, B. (2003) and Grunert et al. (2002), to complement the default explanation provided by

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3 Diversified market concentration indices with advantages and disadvantages between each other can be found in the literature. In this text the Herfindahl-Hirschman Index (HHI) has been adopted as market concentration measure, which is obtained by summing the squares of market shares of companies operating in the analysed market and presents a range between 0 and 10,000. A value of zero represents a market in which there is no company. The value 10,000 represents a market monopoly situation, where a single company has 100% market share. When the HHI is above 1,800 market is considered very concentrated. Between 1,000 and 1,800 the market is considered to have some concentration. This is a methodology commonly used by competition regulators to assess the degree of concentration in a market
the financial capital variables. Lehmann, B. (2003) stresses the importance of non financial factors in explaining the default of start-ups, noting that banks have specific default prediction models for these types of firms that make modest use of accounting information.

Especially taking into account the nature of the dependent variable in this study a logit model it was adopted. As pointed out by Altman et al. (2007), it is a methodology that, while not entirely consensual, is very often used in the vast literature on the problem of default, particularly because the dependent variable is binary (default/non default). This method shows good performance, it is easy to apply and, since the parameter estimation is usually performed by the maximum likelihood method, produces estimators with the necessary econometric properties for statistical inference, Lehmann, B. (2003).

The logit model explains the probability of default by estimating a linear equation of the natural logarithm of the odds ratio of two possible events (default/non default) as a function of several explanatory variables. The regression coefficients can be interpreted separately according to the importance or significance that each explanatory variable shows to the estimated probability of default

3.2. Sample Constitution

This study is based on a panel data with information from two sources: the database of a Portuguese commercial bank and the database of the Instituto Nacional de Estatística.

The sample was extracted from a major Portuguese commercial bank’s database under confidentiality agreement. It is from this database that the bank’s internal rating model is built for which will guarantee the accuracy of information that this circumstance requires.
The sample gathers financial and non-financial information from 1430 firms that started-up between 2005 and 2006 and were parties to financial contracts. The sample integrates 53 companies that defaulted during the three years after their creation and 1377 non defaulting companies in that period. The sample integrates companies that were not selected by random extraction, being therefore a convenience sample, which consequently can not be taken as representative of the start-ups of Portuguese economy in relation to their size, industries in which they operate and default percentage. The sample, however, uses all available information, thus justifying its statistical significance, and reflects primarily the population of start-ups of the financial institution with the involved circumstances. The percentage of defaulting companies (3.71%) reflects the typical structure of loan portfolios that contain less than 5% of defaulters, with the resulting estimation problems, as indicated in Lehmann, B. (2003). The disproportion in the sample between defaulters and non defaulters is constant in the literature on this subject, especially when adopting logit modelling.

The information contained in this sample allows the estimation of models defined with data of explained variable and explanatory variables identified at the firm level: human capital and financial capital. The explanatory variables at the industry level, are obtained from Instituto Nacional de Estatística databases through the website: www.ine.pt. The connection between the two parts of the sample will be made from the CAE (Economic Activity Code) of each observed start-up.

4. Results

In this Section we discuss the estimation results of the default explanatory models (presented in Table IV). 7 logit models were estimated related to the credit default probability in the analysis period. First, partial estimations were carried out, taking into account the types in which the explanatory variables were grouped, i.e., the group with financial variables (Models I and II) and the group with human capital variables (Models III, IV and V). Afterwards we tested all explanatory variables simultaneously. We used the backward stepwise method, starting with all variables and ending only with
statistically significant ones. Thus, for the financial variables we begin in the model I and end up in the Model II and for the variables of human capital we begin in the Model III and concluded in Model V. Model VI is the integration of financial and human capital variables that showed significant. We concluded with the Model VII where the variables related to industry environment at start-up were integrated.

Table I presents a comprehensive set of accounting ratios from 5 categories potentially able to integrate the models to be estimated. A selection scheme similar to that used by Altman et al. (2007) was used to identify the statistically more effective ratio within each category. Model I was estimated in this sequence, including as regressors a financial indicator of each category. The Solvability ratio; the Asset Turns ratio and Net Debt to EBITDA ratio were considered statistically significant, but the Working Capital ratio and Earning Power ratio, while assuring the regression coefficients expected signs, were not statistically significant. Of all the potential explanatory variables of financial nature, those that, taken together, best explain the probability of default during the three years after start-up, are those included in the Model II. Tested in individual models each one of these variables is also statistically significant.

Assessing the sample we observe a weak profitability performance of start-ups regardless of their classification as non-defaulter or defaulter. This generalized weak profitability performance in these firms still at an early stage of their existence, may justify the fact that the profitability ratios proposed do not work statistically, penalizing key analytical indicators, such as return on equity or return on assets. Indeed, in the sample, 33% of start-ups have negative net profit in the third year after start-up and 21% have two consecutive years of negative net profit.

Evidence was found for a significance level of 1% to the fact that the greater the extent to which the company uses equity in financing their activity on total liabilities, that is, the greater the owners personal commitment of financing the company in a very early stage of their life cycle, the lower the probability of the companies defaulting during the three years after start-up. The financial autonomy ratio has also expressed statistical robustness in the determination of default behaviour.
Simultaneously, in the same direction and with the same statistical strength it can be concluded that the more efficient the use of assets under management, the lower the probability of occurrence of an internal credit event in a company’s early life. It was also possible to obtain statistical evidence to accept the hypothesis of a positive relationship between the net debt recovery period and credit default. The start-ups’ default probability in the first year of existence is less the greater the extent to which the ability to generate EBITDA covers net debt.

To attempt to control the size effect in the estimated models the natural logarithm of net assets and the natural logarithm of turnover was used. The use of these mechanisms was statistically irrelevant.

In Model III the five proposed explanatory variables related to human capital were tested. The variables schooling and management experience have high statistical significance, either when tested in individual models, or when they are integrated together in the Model V. These results align with those of Santarelli et al. (2007), in which specific education and management and business experience prove to be related to an above average post-entry performance. Likewise, the Baptista et al. (2009) work results for the Portuguese economy for the period between 1986 and 2005, in which they concluded that founders of start-ups with more education are more likely to succeed.

It was therefore possible to obtain statistical evidence that allows for discarding the hypothesis of absence of relationship between the rates of human capital held by the founder at a start-up’s constitution, both in general dimension, and in the specific dimension, and the probability of credit default. A founder’s schooling levels and management experience background, which could be expected to negatively influence the credit default probability, were statistically significant.

The variable related to schooling was changed in Model IV. Specifically we tried to capture the effect of higher education in the behavior of credit default. The model
therefore considered a qualitative binary variable that displays the value 1 if the founder has a higher academic degree or 0 otherwise. The statistical results show up in line with the results obtained from previous models. We found strong statistical evidence regarding the effect of higher education in mitigating the risk of default. Founders with higher level of education reduce the level of credit loss ratio in start-ups.

A founder’s experience in the sector contains an entrepreneurship feature more heterogeneous than the management experience. The management experience points to an entrepreneurial initiative more driven by a recognition of an opportunity (Opportunity-based), the experience in the sector includes, in addition to this motivation, an entrepreneurial initiative influenced by necessity (necessity-based). We therefore admit, in the face of the founders experience in the sector greater heterogeneity, some statistical inefficiency of this explanatory variable, and that although they match the expected regression coefficient signal they were not statistically significant.

Variables related to industrial dynamics at boot time were not capable of complementing the explanatory power of the variables mentioned above, according to Model VII.

5. Conclusions

In this paper we analyze the credit default behavior in start-up companies. In a tracking period of three years after start-up, we tested the behavior of the first credit event related to financial contracts in which the start-up company was borrowing, against a set of factors recognized by the literature as likely to influence survival and the default of companies. Thus, from a panel data of 1.430 start-ups and using logit modeling, we

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4 The Global Entrepreneurship Monitor splits entrepreneurship into opportunity-based and necessity-based as a way to distinguish the start-up motivations that result from the recognition of an opportunity, from those that are triggered by lack of occupational choice.
came to several conclusions about the impact on credit default produced by variables grouped into three types: financial capital, human capital and industrial dynamics.

We concluded that in newly created companies, the support provided by partners in financing the activity proved statistically decisive in mitigating default risk. In addition to this hard fact, there is a double circumstance associated with start-up businesses, especially relevant in a statistical sense in limiting the likelihood of credit default: on the one hand, the intensity of the use of a company’s assets under management, measured by the increased assets coverage by turnover; on the other hand, the net debt coverage by EBITDA. Start-ups which have activity volumes that ensure high asset turns and have short net debt recovery periods, statistically secured better performance in relation to the timely fulfilment of their financial obligations arising from credit agreements.

We additionally verified that the occurrence of an internal credit event in a financing agreement at an early stage of the life cycle of the company is further limited the greater the human capital rate held by the project promoter, in terms of schooling and management experience. We also found complementary that the founder’s high education reduces the start-ups credit loss ratio level.

The management experience and academic qualifications background recognized in the literature as having solid gains in terms of learning ability, business detection opportunities and organizational skills, are qualitative risk factors (soft facts) that can demand the attention of the credit decision maker in the analysis of start-ups financing operations. It does not mean that human capital as a soft-fact is the only feature associated with the start-up founder that should be considered in the decision process. However, its relevance shows to be statistically significant. It should be noted that in this work alternative factors such as a founder’s property portfolio, or their ability to access capital, were not weighed and other factors, like eventual collateral, guarantees, contracts, or other mitigation credit risk methods were not considered as in Lehmann, B. (2003).
The credit risk in start-up companies, measured by the first credit event, was sensitive to risk factors related to financial capital and human capital, but was not sensitive to the variables related to the industrial dynamics context at the start-up. The variables at the industry level were not able to complement the explanatory power of the other variables considered, nor demonstrated statistically significant when tested in individual models.

Considering the importance that technology-based start-ups today play in promoting innovation, technological development and competitiveness, and considering that the risk and uncertainty associated with these types of projects represent a constrain on access to bank funding, the next research step may lok into the examination of the determinants of credit default in this specific segment of companies.
### Table V

**Estimation Results - Logit models of the probability of credit default**

<table>
<thead>
<tr>
<th>Model</th>
<th>Solvability Ratio</th>
<th>Asset Turnover Ratio</th>
<th>Debt to Ebitda Ratio</th>
<th>Working Capital Ratio</th>
<th>Return on Sales Ratio</th>
<th>Schooling</th>
<th>Management Experience</th>
<th>Industry Experience</th>
<th>Success on Previous Projects</th>
<th>Business Plan</th>
<th>Industry Growth</th>
<th>Entry Rate</th>
<th>Industry Concentration</th>
<th>Constante</th>
<th>Nº de Observações</th>
<th>Log likelihood</th>
<th>R-Squared</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>-1.278***</td>
<td>-0.500***</td>
<td>0.011*</td>
<td>-0.145</td>
<td>-0.004</td>
<td>-0.182**</td>
<td>-0.042**</td>
<td>-0.006</td>
<td>0.262</td>
<td>0.128</td>
<td></td>
<td></td>
<td></td>
<td>-2.458***</td>
<td>1428</td>
<td>-212.97</td>
<td>0.060</td>
</tr>
<tr>
<td>II</td>
<td>-1.424***</td>
<td>-0.495***</td>
<td>0.011*</td>
<td>(1.304)</td>
<td>(0.610)</td>
<td>-0.654**</td>
<td>-0.041**</td>
<td>-0.006</td>
<td>0.246</td>
<td>0.133</td>
<td></td>
<td></td>
<td></td>
<td>-2.590***</td>
<td>1428</td>
<td>-213.3</td>
<td>0.059</td>
</tr>
<tr>
<td>III</td>
<td>-1.390***</td>
<td>-0.495***</td>
<td>0.011*</td>
<td>(1.288)</td>
<td>(0.316)</td>
<td>-0.254***</td>
<td>**</td>
<td>(0.404)</td>
<td>(0.894)</td>
<td>(0.418)</td>
<td></td>
<td></td>
<td></td>
<td>-2.202***</td>
<td>1430</td>
<td>-222.46</td>
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<tr>
<td>IV</td>
<td>-1.409***</td>
<td>0.011*</td>
<td>0.012*</td>
<td>(1.348)</td>
<td>(1.378)</td>
<td>-0.917</td>
<td>-0.040**</td>
<td>(2.166)</td>
<td>(2.099)</td>
<td>(2.033)</td>
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<td>-2.789***</td>
<td>1430</td>
<td>-221.4</td>
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<td>V</td>
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<td>VI</td>
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<td>-1.705***</td>
<td>1428</td>
<td>-209.64</td>
<td>0.075</td>
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<td>VII</td>
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<td></td>
<td>-1.318***</td>
<td></td>
<td>-208.20</td>
<td>0.081</td>
</tr>
</tbody>
</table>

(values in parentheses are amostral results of "t statistics")

*** - significance level of 1%

** - significance level of 5%

* - significance level of 10%

(a) In scholling it was considered a dummy variable related to higher education (Bachelor or more)
References


*Global Enterpreneurship Monitor*, Relatório de 2010


