Universitat Internacional de Catalunya
Programa de Doctorat en Economia i Dret

Tesis doctoral

Which start-ups do accelerators prefer?

A comprehensive approach

Ricardo Torrecilla Sánchez

UNIVERSITAT INTERNACIONAL DE CATALUNYA

WHICH START-UPS DO ACCELERATORS PREFER?

A COMPREHENSIVE APPROACH

Submitted by: Ricardo Torrecilla Sánchez

Thesis Directors: Dr. Jasmina Berbegal-Mirabent & Dr. Yannis Pierrakis

A doctoral thesis submitted in fulfilment of the requirements of Universitat Internacional de Catalunya, UIC Barcelona, for the degree of Doctor of Philosophy

Barcelona, 2nd November 2022

Table of Contents

List of Tables

List of Figures

Author's declaration

I declare that:

Except where explicit reference is made to the contribution of others, this dissertation is the result of my own work and has not been submitted for any other degree at Universitat Internacional de Catalunya, UIC, or any other institution.

The reproduction of any part of this thesis for teaching or in academic or other forms of publication is subject to the limitations on the use of copyrighted materials and to the proper and full acknowledgement of the source.

The digital version of the thesis I am supplying is the same version as the final one, hard-bound copy submitted in completion of my degree, once corrections have been completed.

I have exercised reasonable care to ensure that the thesis is original and does not to, the best of my knowledge, break any Spanish law or other Intellectual Property Right or contain any confidential material.

Signed:

Ricardo Torrecilla

Acknowledgements

This is a special occasion but the same could not have been possible without the help of others.

First, I thank Dr. Marta Mas, the dean of the Facultad de Ciencias Económicas y Sociales at UIC, for opening the doors of this University for me and for treating me as if I were a peer since the very first moment. My sincere thanks to Dr. Frederick Marimon too, for his constant support and kindness, especially in difficult moments.

I also want to thank Dr. Ramon Bastida, who first introduced me to the topic and gave me initial guidance and good advice. Dr. Jasmina Berbegal-Mirabent and Dr. Yannis Pierrakis, have played, of course, the central role of this journey. This thesis would not have been possible without their stimulus, guidance, and their patient review of the subsequent versions.

I want to express my gratitude to Dr. Toni Mora and Dr. David Roche too. Not only are they an instance of the highest professionalism and willingness but evidence that research is not at odds with kindness and witty banter.

Finally, all the efforts of the aforementioned people, although of the utmost importance, would not have been enough for this day to come without the love and encouragement of Clara and Roger, my daughter, and my son.

Abstract

The purpose of this thesis is to investigate the role played by both the human capital of founders and the financing sources in startups, whether they are impactful or just for-profit ventures, in the odds of being accepted in a business accelerator, considering both for-profit and impact-driven programs. In the present investigation, the human capital is considered to be composed of three dimensions, namely, educational background, previous managerial experience, and previous founding experience, and the same division into three categories also applies to the financing sources: debt, equity, and philanthropy. We use the 2020 GALI Database from Emory University, which features more than 400 business accelerators and over 23,000 team applicants worldwide, which are grouped into four world income areas. For the data analysis, in addition to traditional econometric methods, we also use big data techniques such as decision trees and association rules. Our findings point to the greater importance of financing sources relative to the human capital endowment of entrepreneurs when it comes to accelerator acceptance. In particular, the presence of either bank loans or angel equity on the balance sheet of the scrutinized firms, which suggests that accelerators may endorse the commercial banks and business angels' screening criteria. It is interesting to note that both sources of financing do not normally appear together in ventures which participated in a program. Nevertheless, human capital does still play a relevant role when properly combined with other startup characteristics, especially with the financing sources mentioned above. The profile of the startups sporting credit from banks or equity infusions from angels are completely different.

Keywords: accelerators, human capital, financing sources, big data, association rules.

Resumen

El propósito de la presente tesis es investigar el papel que desempeñan el capital humano de los emprendedores y la estructura de capital de sus respectivas empresas, ya sean estas organizaciones con ánimo de lucro o entidades que también persiguen un determinado impacto social o medioambiental. En este trabajo, el capital humano está representado por tres dimensiones distintas, a saber, educación, experiencia directiva previa, y también experiencia en la fundación de empresas. Asimismo, la estructura de capital de las empresas se dividirá en tres clases que son, fondos propios y capital aportado por terceros, deuda, y fondos provenientes de organizaciones filantrópicas.

Los datos empleados han sido obtenidos de la 2020 GALI Database de la Emory University, base de datos que incluye más de 400 aceleradores de empresas y más de 23.000 startups de todo el mundo, las cuales se han dividido en 4 áreas de acuerdo con la renta per cápita de las mismas. Los mencionados datos han sido analizados usando tanto técnicas econométricas tradicionales como también los más avanzados métodos de Machine Learning, como son los Árboles de Decisión y las Reglas de Asociación.

Nuestros resultados apuntan a una mayor relevancia de las distintas fuentes de financiación por encima de la dotación de capital humano de los emprendedores. En particular, destaca la presencia de préstamos bancarios o de inyecciones de capital por parte de business angels. Tales hallazgos sugieren que los programas de aceleración de empresas pueden adoptar, aunque sea parcialmente, los criterios de selección empleados en su momento por los proveedores de fondos mencionados.

Vale la pena recalcar que esas dos fuentes de financiación no aparecen normalmente juntas en la misma empresa. A pesar de lo mencionado, señalamos también que la importancia del capital humano no desaparece cuando se consideran también las fuentes de financiación, si no que adquiere precisamente su significación junto a algunas de estas. De especial interés

son los dos perfiles de start-ups, las financiadas por préstamos bancarios y las respaldadas por business angels, los cuales con radicalmente distintos.

Palabras clave: aceleradores, capital humano, fuentes de financiación, big data, reglas de asociación

1. Introduction

1. 1 Research Problem

Accelerators are an innovative funding mechanism that first appeared in 2005 (Cohen & Hochberg, 2014) with the foundation of the first of its class in the US. Since then, accelerators—also referred to as seed accelerators or accelerator programs—have spawned across the globe (Fehder & Hochberg, 2014). Amongst the reasons for this growth we can find the increase in the knowledge-intensive component of many of the new business models that are currently emerging, fueled, in turn, by a dramatic reduction of experimentation costs through the technological and digital revolutions in which we are immersed (Ewens et al., 2018), and improvements in management practices, such as the lean approach that may shorten both the time span and the needed resources to convert a business idea into a minimum viable start-up (Stayton & Mangematin, 2019).

Business accelerators have already been addressed by scholarship from several different perspectives: their effect on the treated firms' growth and survival (Del Sarto et al., 2020; Dvoulety et al., 2018; Kerr et al., 2014), their impact on the chances of raising subsequent financing and on its amount (Regmi et al., 2015), their role in market infrastructure development (Dutt et al., 2016; Fehder & Hochberg, 2018), their fit along the venture creation pipeline (Yang & Kher, 2018), how they may enhance the reputation of the entrepreneurs themselves (Mansoori et al., 2019), or how they may speed up exit through either acquisition or failure (Arora & Nandkumar, 2011; Winston-Smith & Hannigan, 2017). However, there is still a significant knowledge gap regarding the selection criteria in general (Pierrakis & Owen, 2020) considering both the human capital endowment of the entrepreneurs and the financing sources of the firms. We address this gap here.

Accelerators are reported to select their cohorts through highly competitive processes (Clarysse et al., 2016; Winston-Smith et al., 2015). Yet, when shifting the lens to the characteristics of the entrepreneurs themselves and to the financing sources, little has been said except for some references to the education of the founders and to the business growth for those startups raising subsequent follow-on financing after accelerator participation (Lall et al. 2020), and other qualitative attributes such as strong leadership, commitment, and willingness to learn (Hoffmann & Radojevich_Kelley, 2012). This knowledge gap opens up opportunities for research and enables the formulation of our research problem. Specifically we inquire whether there is an ideal start-up profile when it comes to accelerator acceptance.

Aiming to shed new light on this specific matter, to the best of the authors' knowledge, this study improves our understanding on the selection criteria that accelerators use. More specifically we dive deeper into how programs react to both the professional and educational background of the applicants on the one hand, and on the relevance of the ventures' capital structure on the other. That is, the extent to which those characteristics of the entrepreneurs and of the financial mixture of the firms influence the decision of being accepted in an accelerator, and consequently, their importance in the likelihood of receiving follow-on investment in future steps in the start-up process. Thus, the assessment of the relative importance of those qualitatively distinct attributes of startups could shed additional light on the still unresolved debate in the entrepreneurial finance arena: *Who are the accelerators betting on, the jockey or the horse?*

1.1.1 Research Question 1

As startups are usually ventures not fully fledged, sometimes just little more than a business idea, and therefore, presumably lacking additional signs of quality other than the human capital of their founders (Hsu, 2007; Pierrakis and Owen, 2020), we first focus on the reaction of accelerator programs in front of the characteristics of the entrepreneurs themselves. Specifically, we articulate our first research question as follows: *What is the role played by the human capital of the founders in the likelihood of being accepted in an accelerator?*

To answer this question, we analyze that human capital proxied by three key dimensions: higher education, senior managerial experience, and founding experience which are widely supported by the extant literature.

1.1.2 Research Question 2

Since academics also support the idea that the most important characteristics of start-ups are not only the education and experience of their promoters, but its sources of financing too, and that the relative importance of the different financing sources increases over time (Kaplan et al., 2009), we conduct a stepwise analysis and broaden the focus to include the capital structure of the applicants as well. Therefore, we take into account whether those firms that were accepted in accelerator programs had raised money from lenders, equity investors, or philanthropic funders, either professional or casual, prior to the application date. Particularly, we want to compare the relevance of the human capital endowment on the one hand, and the importance of the capital structure elements on the other. Accordingly, our second research question can be formulated as: *What matters most, the human capital or the funding structure?* We find this question of the utmost importance to shape what the ideal star-tup profile is.

1.2. Objectives

We consider the analysis of how accelerators select their candidates of paramount importance as follow-on investors frequently endorse the screening performed by programs on their portfolio companies (Kim & Wagman, 2014). Moreover, understanding the underlying mechanics how programs pick their investees may help the entrepreneurial ecosystem reach a sound equilibrium: available funds, whether public or private, and whether professional or occasional in origin, should go to those ventures with reasonable prospects of deploying their business plans successfully. Accordingly, the objective of this thesis is to investigate the ideal startup profile for being accepted into an accelerator program. Subsequently, it can be further divided into a series of specific objectives.

Objective 1. This objective entails the thorough review of the extant literature on the aspects that affect the most our research problem. What scholarship has written about the human capital endowment of those who want to become entrepreneurs, and what has been said with respect to the relevance of the capital structure of nascent ventures. Furthermore, we also review the connection between those factors against the backdrop of the signaling theory. What is first perceived by program managers, or what is considered more important, when they select candidates for their portfolios.

Objective 2. Much has been said in the last decades with respect to the personal characteristics of business owners and of those who engage in entrepreneurship. Surprisingly though, the result of that considerable research is inconclusive. Sometimes, it is certain characteristics that seem to have the greatest relevance for successfully running a business or for raising funds, whereas in some other occasions those same characteristics are either displaced by other factors, which become more prominent, or simply vanish. In this second objective we intend to shed light on the true and especially separate relevance of our focal human capital dimensions relative to entrepreneurship, and for that purpose we believe that traditional Econometrics is the most appropriate methodology.

Objective 3. Once the relevance of each dimension of human capital has been tested, we subject these dimensions to an additional stress test, considering now the whole start-up profile, i.e., both the human capital endowment of the team and the different sources of financing of the company. In the first phase of this two-stage objective, we rely again on Econometrics, to produce a fairly homogenous comparison among all startup ingredients. However, the second phase entails a radically different strategy. Although econometrics needs no defense whatsoever, it lacks the ability to outline complete profiles. Probabilistic models such as Probit and Logit effectively assign values for each component in the regressions, but those values attest just the effect of the presence or absence of the focal characteristic in the model. Conversely, that is precisely the ability of Big Data techniques. The novelty of our approach lies in the fact that it allows complete startup profiles to emerge to the surface, through an unparalleled holistic approach, by using Machine Learning techniques: decision trees and association rules. We do not seek to measure only the effect of a set of startup characteristics on a stand-alone basis each, which is what Econometrics can register. Rather, we aim at finding what set of characteristics taken together shapes the most sought-after startup profile.

Table 1 portrays a summary of the research problems, objectives, and methods.

Table 1. Summary of research questions, objectives, and methods

Research Objective	Research Question	Methodology	Chapter in the Thesis
Objective 1. Thorough review of the Literature	-	Systematic review of the literature	2
Objective 2. The separate relevance of human capital (HC) dimensions	What is the role of the HC in the likelihood of being accepted in an accelerator?	Regression analysis (Probit)	4.2
Objective 3. The relative relevance of the HC and the capital structure	What matters most, the HC or the funding mixture?	Regression analysis (Probit)	4.3
		Machine Learning	5

For assessing the relevance of each selected human capital variable and of each financing source, we use data from the 2020 GALI Database, the Entrepreneurship Database Program at Emory University, which gathers information from over 400 accelerators worldwide. The use of this database is backed by recent research (Lall et al., 2020; Pierrakis & Owen, 2020; Venâncio and Jorge, 2021).

We envision obtaining relevant outcomes from our analyses. First, we expect to confirm the positive role of human capital, particularly of education, which would be consistent with the broad support from the extant literature (Nielsen, 2015; Ratzinger et al., 2018). We also expect strong support for the financing sources variables, especially for debt, amply backed by scholarship likewise (Cole & Sokolyk, 2013; Robb & Robinson, 2014).

1.3. Structure of the Thesis

The remainder of this thesis is structured as follows. Chapter 2 reviews the relevant literature about human capital and on the capital structure and the financing sources of companies putting the stress on startups. The related theories are exposed for presenting the theoretical backcloth against which the hypotheses are developed. The data collection, the method, and the variables are described in Chapter 3. Chapter 4 describes the model specifications for the econometric regressions and their results. Chapter 5 moves on to Big Data. Chapter 6 features a reconciliation of results, i.e., Econometrics versus Big Data, similarities, dissimilarities, and complementarities. Chapter 7 describes the robustness tests implemented in this study. Chapter 8 presents the discussion of the investigation. Finally, Chapter 9 indicates limitations of this research and suggests further research.

2. Literature Review

2.1 Signaling Theory and its Applications to Entrepreneurship

Signaling Theory (Spence, 1973) helps describe the behavior between two parties when those parties have different information on one same thing. Signalers are insiders who possess information about something which is not observable to others, the receivers, who are outsiders. Thus, signaling focuses fundamentally on sending deliberately positive information about the qualities of an organization, a candidate, etc., the signal, although signals can also be emitted inadvertently as a consequence of the insiders' attributes or actions. Furthermore, outsiders are not strictly passive receivers as they may also select what signals to focus on and what can be interpreted from those signals. For instance, as unveiled by Spence (1973) in his seminal work, job recruiters deemed higher education a desirable quality not just because of its presumed impact on the candidates' productivity but because it reflected some of their personal qualities too. Higher education signaled positively the ability of highly-educated candidates because they succeeded in overcoming the rigors of attaining it. Therefore, signaling is primarily concerned with the reduction of information asymmetry (Stiglitz, 2202), i.e., the conflict between those who possess all the relevant information and those who would make better decisions if they had it.

Signaling theory plays a pronounced role in the management and financial literature in general and in the entrepreneurship research in particular. By way of illustration and to cite just a few examples, it could be mentioned the works of Ross (1977) in financial structures, Certo (2003) on the influence of boards on exits via IPO, Amaral and Baptista (2009) on the impact of human capital and serial entrepreneurship, Bublitz et al. (2018) on the effect of entrepreneurs' qualifications and their income, Colombo (2020) about the use of signals in entrepreneurial financing, etc.

Accordingly, signaling theory, along with other views of both the firm and the entrepreneurs, will be the main theoretical underpinnings of our research, as we try to disentangle the ideal startup profile out of a considerable array of founder and firm characteristics.

2.2 Human Capital through Signaling Theory and other Views of the Firm

Information asymmetry may cause both entrepreneurs and accelerators to face adverse selection that could lead them to suboptimal decisions when pondering whether to enter a certain program or when considering the acceptance of a team within their cohorts, respectively. From now on, we adopt the accelerator's perspective and focus on the signals they may use to reduce that asymmetry.

The relative importance of teams is consistent with the resource-based view of the firm (Penrose, 1959), which depicts companies as bundles of resources and capabilities whose aim is to grow the company. Barney (1991) stresses that for a resource to contribute to the implementation of the strategy of a business and the creation of a sustainable competitive advantage, that resource must possess, among other features, rareness, as well as being imperfectly imitable, which suggests that its mere presence is not a sufficient condition for attaining the desired results, but it must have certain differentiating qualities. Furthermore, the critical resource view (Zingales, 2000) goes so far as to argue that in the last decades human capital has become firms' most valuable asset. Be that as it may, those views suggest that the experience and skills possessed by team members such as education, managerial experience, and founding experience can be critical success factors for nascent ventures (Colombo et al., 2004; Unger et al., 2011). What is more, as earlier mentioned, the human capital embodied in a team might not be the only circumstance *per se* that would render a candidate preferable to another. Rather, it might also convey additional signals of prowess otherwise unobservable to the receiver (Colombo, 2020). It is less probable that lower-quality applicants could have gathered such capital (Connelly et al., 2011).

High-talented teams bear greater opportunity costs relative to other teams with a lower human capital endowment when choosing entrepreneurship (Gimeno et al., 1997; Nielsen, 2015). Every time a team must decide on a new external equity infusion, it is as if the founders have purchased a real option on their own business whose price will be lower, as the entrepreneurs' opportunity costs are higher (Arora & Nandkumar, 2011), which, in turn, represents an extra risk on top of the inherent business risk already borne by the intermediary when it agrees to supply the much-needed funds. Highly endowed entrepreneurs might decide not to continue and find an alternative career path (Baptista et al., 2014) if the services offered by the intermediary, including financing, or their perceived chances of success fail to meet their expectations (Yu, 2019). In contrast, teams with valuable outside opportunities that choose to commit themselves to their projects send a very powerful signal (Spence, 1973) to their prospective funding partners that may lessen somewhat that risk to abandon (Rider et al., 2019).

Indirect additional support to the former views can be found in one of the defining characteristics of human capital: its inalienability (Hart & Moore, 1994). As human capital cannot be detached from those who possess it, companies should organize themselves around other resources, which could somewhat alleviate that implicit threat. However, the claimed primacy of human capital over all the other firm resources could be deemphasized to some extent. Some winning start-ups, ventures that went public successfully, showed relevant human capital turnover, the replacement of the CEO and other key positions, whereas their initial business plans only suffered minor changes (Kaplan et al., 2009). Still, the support for that primacy may not have faded away altogether: when submitted proposals, seasoned business angels seemed to react to team information only, whereas novice angels reacted to both team characteristics and other information about the company (Bernstein et al., 2016).

The above arguments reveal that the resource around which a company must organize itself is still an unresolved debate and that, probably, different investors, through accrued experience, may have found that different screening criteria could better serve their interests.

Since Mincer (1958) first highlighted the positive relationship between years of education and of work experience on the one hand, and of wages on the other, human capital has been repeatedly reported to be beneficial not only to the work environment, but to entrepreneurship as well (Estrin et al., 2016; Obisi & Anyim, 2012; Ratzinger et al., 2018), and its role has been tested through a wide array of constructs, which usually include work experience, education, entrepreneurial experience, and demographic and psychological factors (Marvel et al., 2016). For the purpose of this work, human capital is a construct that comprises three dimensions, namely, higher education, previous managerial experience, and previous founding experience.

2.2.1 Higher Education

The importance of education may extend to the two phases of entrepreneurship: opportunity recognition and exploitation (Shane & Venkataraman, 2000). Education seems to have a close and positive relationship with the foundation of new businesses (Samuelsson & Davidsson, 2009) and its breadth increases the chances of becoming an entrepreneur (Mackiewicz & Kurczewska, 2020). Education has also been found to be a relevant factor for both the firm's initial size (Colombo et al., 2004) and for business survival (Mackiewicz & Kurczewska, 2020). Once within the accelerator sphere, there seems to be a positive correlation between the levels of education and venture creation (Peña, 2004) on the one hand, and the amount of follow-on funds raised on the other (Ko & Mckelvie, 2018; Winston-Smith & Hannigan, 2017).

Formal education can also be essential in social entrepreneurship as it frequently occurs in underdeveloped areas, which may lack basic infrastructures, business institutions, and sometimes even markets themselves, and where structural change can be the norm rather than the exception (Honig, 2001), because it is believed to enhance the entrepreneur's cognitive abilities even more effectively than other types of human capital: a broader knowledge base would be preferred to past experience (Unger et al., 2011). Accelerators can be particularly useful in helping develop those markets thanks to the entrepreneurial schooling they provide (Gonzalez-Uribe & Leatherbee, 2018).

Investing in start-ups is not the mere infusion of money to expected high-yielding allocations. Rather, it entails allocating resources to nascent ventures whose prospects will be to a large extent in the hands of those who manage them. Therefore, intuition in venture investment does play a role (Ebbers & Wijnberg, 2012). Founders' higher education may help disentangle the subjective part of that decision-making through the perceived signal of commitment attached to it (Achleitner et al., 2013). Therefore, according to the above, we hypothesize that:

Hypothesis 1: *The effect of higher education within a team will increase the likelihood of being accepted into an accelerator.*

2.2.2 Managerial Experience

Prior managerial experience is said to contribute positively to increasing both the performance of individuals in their current job positions (Davidsson & Honig, 2003), and the probability of success in entrepreneurship (Staniewski, 2016). Founders with experience in the most senior positions are more likely to IPO and raise more money (Jones, 2020). Scholars have also considered business experience to be essential for the development of underdeveloped areas as well, because, in addition to leading to higher levels of productivity, the normally resource-constrained framework within which nascent firms struggle could be somewhat more easily overcome by those entrepreneurs with a talent for management. Seasoned managers would be, thus, believed to design better business strategies (Bruhn et al., 2010). Conversely, managers with prior managerial experience in not-for-profit organizations only would not be expected to perform well in for-profit environments because they would not be fully aware of the need for financial sustainability (Beaton, 2021).

Similarly, industry-specific experience is positively related to business survival (Shu & Simmons, 2018) and to higher rates of entrepreneurial success (Azoulay et al., 2020). In the same vein, specific experience may have a positive impact on both firm value and performance (Dass et al., 2014) and it is also believed to help innovation, especially in small firms (Balsmeier & Czarnitzki, 2014). However, Samuelsson and Davidsson (2009) claimed that industry experience can be both an asset and a liability depending on whether that experience and the new venture belong to the same sector, and Tian (2011) found that those positive effects could dilute when it comes to managing diversified businesses. Moreover, some of those beneficial effects could be precisely so when specific experience is combined with experience from other sectors within the same entrepreneurial team (Honoré, 2020). Thus, the debate, perhaps, should not be what type of experience is more important but in which scenario each of them would be more effective (Dencker & Gruber, 2015; Estrin et al., 2016). Therefore, despite the fact that there are some arguments that could understate the relevance of managerial experience, we posit that prior managerial experience could ease program admission.

Hypothesis 2*: The effect of managerial experience within teams will have a positive impact on the likelihood of being accepted into an accelerator.*

2.2.3 Previous Founding Experience

Even though some of the skills and knowledge that are necessary for running a business can be acquired through formal education (Bruhn et al., 2010), it is the experimental nature of start-ups that has caused previous start-up experience to be repeatedly cited as beneficial to entrepreneurship, providing much of what is needed through learning-by-doing (Lafontaine & Shaw, 2016).

Individuals with prior founding experience are often referred to as serial entrepreneurs and that condition is normally granted to those who have founded at least one business before (Amaral et al., 2011). The extant literature reports positive effects related to this type of experience. It may give insight into the internal organization required by a new firm and into the market where it will operate (Delmar & Shane, 2006), and, relative to ventures founded by novice entrepreneurs, new firms created by serial founders may have higher chances of survival (Baptista et al., 2014), higher sales and productivity (Shaw & Sorensen, 2019), may be more innovative (Vaillant & Lafuente, 2019), and may obtain higher valuations and raise more money in follow-on funding even if their founders' previous experience has been unsuccessful (Nahata, 2019).

On the other hand, the mere possession of founding experience, regardless of the number of firms previously founded, cannot guarantee the success of the new venture (Ye, 2017). For instance, Gottschalk et al. (2014) find serial experience to be unrelated to firm survival, and Nahata (2019) reports that serial entrepreneur-backed companies have lower performance than novice-backed ones. Usually, entrepreneurs rely on heuristics more than the managers of well-established firms do (Shepherd et. al 2015) and although heuristics can help in contexts of high uncertainty (Gilbert-Saad et al., 2018), serial founders may tilt their decision-making too much towards it in comparison with novice entrepreneurs. They might be too tempted to apply well-known recipes to situations requiring innovative approaches (Ye, 2017), with the ensuing additional risk due to oversimplification (Ucbasaran et al., 2008).

Moreover, even though the presence of behavioral biases does not necessarily have to be negative (Zhang et al., 2020), researchers also suggest that serial entrepreneurs may misperceive risk due to both overconfidence and over-optimism (Kambourova & Stam, 2017; Zhang & Cueto, 2017), which may lead to a defective business performance forecast relative to industry-specific experience (Cassar, 2014).

According to the previous arguments, and due to the habitual structure of accelerators, which conveys entrepreneurial knowledge mainly through mentors, we argue that accelerators may be more interested in requiring unexperienced teams, as they will benefit more from an accelerator course than experienced teams. That is, previous experience may somehow encumber the efficient transmission of that accrued knowledge to participants who might inadvertently be somewhat reluctant to accept others' expert advice simply out of inertia. Accordingly, we hypothesize that:

Hypothesis 3*: The effect of prior founding experience within teams will have a negative impact on the likelihood of being accepted into an accelerator.*

2.3 Capital Structure through Signaling Theory and other Views of the Firm

Even though it was Ross (1977) who first applied signaling theory on the determination of the capital structure of a firm, the inescapable starting point of any discussion about the issue still is the first work of Modigliani and Miller (1958) in which they posited that in a world with no taxes on income the funding mixture, i.e., the proportion of debt and equity on a firm's balance sheet, was irrelevant. Such an extreme an unrealistic assumption prompted the authors themselves to correct its own work (1963) but their propositions still implied informationally efficient markets and no bankruptcy costs. Subsequently, Kraus and Litzenberger (1973) in their Trade-Off Theory addressed the issue of the value of the tax shields, the deductibility of the interest charge for taxation purposes. If leverage increases the value of the firm through higher tax shields, why not a capital structure of only debt, then?

Because of the existence of bankruptcy costs, the perceived increased risk by stakeholders who would fear that the high-leveraged firm could not honor its contractual obligations.

All the above argumentation presupposed that the management duly fulfilled their fiduciary duty, i.e., to act in the best interest of the shareholders, something that was openly questioned by Agency Costs Theory (Jensen and Meckling, 1976), which argues that ownership structure may condition the capital structure of the firm through the relationship between owners and managers on the one hand, and owner-managers and creditors on the other. This could be considered the closest that the theoretical building of capital structure had come to the reality of small firms and startups, which normally do not have access to public capital markets for securing the funds they need, and who, consequently, may not have the financing structure that they wish but the financing mix that they might have, until Myers and Majluf (1984) developed their Pecking Order Theory.

Pecking Order Theory posits that information asymmetries may condition the capital structure of firms. Firms would not have the purportedly ideal capital structure at a certain business growth stage but, rather, they would have a financing mixture that would correspond to its current degree of opacity, establishing an order in which internal financing would come first, debt afterwards, and last, equity infusions. The underlying rationale of such a sequence is clear. Internal financing, the positive cashflow stream yielded by the firm, conveys no informational asymmetries between managers or manager-owners and external fund suppliers. In contrast, both equity and debt do. Consequently, once the cash reserves turned by the normal operation are depleted, the managers of the company would turn to debt because it is a cheaper financing source relative to equity infusions. The scrupulous screening and monitoring of credit applicants by professional money-lenders helps alleviate to some extent the information gap between insiders and outsiders enabling a lower compensation for the latter. The board would use equity only as a last resort due to its high cost. Equity investors bear the highest risk possible. While it is true that they can earn unlimited upside benefits, they are also just residual claimants on the cashflow turned by the company. They are paid only once all the other senior claimants have been made whole, which entails a much higher compensation, the discount offered on the newly issued shares. Recent empirical evidence (La Rocca et al., 2009; Cosh et al., 2009; Serrasqueiro and Caetano, 2015) gives support to that pecking order although not unanimously (Robb and Robinson, 2014; Hechavarria et al., 2016). The accelerator phenomenon itself may suggest to some extent a reversal of the Myers and Majluf's tenets (Pierrakis and Owen, 2020) when taking stakes in their investees in exchange for a modest equity infusion despite the high information asymmetry present.

Similarly, Financial Growth Cycle Theory (Berger and Udell, 1998) formulates that the capital structure of firms evolves over time driven by the degree of informational opacity. At first, nascent firms make use mostly of insider financing sources, i.e., equity and debt from the founders and their families and friends, and internal financing if any. As the start-up gets more traction and the opacity relaxes, those almost exclusively insider sources may shift gradually into external ones. Even though their propositions have found scholarship support (Sánchez-Vidal and Martin-Ugedo, 2012; Cotei and Farhat, 2017) the authors themselves emphasize that their growth cycle may not fit well all type of start-ups. The capital structure is not neutral either. The presence of certain financing sources on the balance sheet may convey powerful signals to the appropriate receptors (Ross, 1977), which may facilitate further endorsement by follow-on investors (Kim and Wagman, 2014; Berstein et al., 2016; Ko and McKelvie, 2018). Last, the choice of the capital structure goes far beyond a mere question of cost-effectiveness, especially in the earliest stages of the business cycle because it may have a noticeable impact on the successful development of startups (Cosh et al., 2009; Cole and Sokolyk, 2013; Hechavarria et al., 2016).

2.3.1 Internal financing

The generation of internal cashflow can be of one the first and most powerful signals of the nascent business' prospects in the very tight resource-constrained framework in which startups should develop. In addition to conveying no informational asymmetries, internal financing is also widely reported by scholarship as a reliable indicator of the financial health of any type of business, nascent startups included. It is said to increase the flexibility of the management for running the firm (Myers and Majlluf, 1984; Graham and Harvey, 2001) through preserving their financial and decision-making autonomy across all the venture's growth stages (Fadil and St-Pierre, 2021), and to enable a better allocation of investment projects (Blau and Fuller, 2008). From the fledging venture's point of view internal financing, understood as one of the ingredients of the bootstrapping mix, could be a matter of strategic choice rather than a question of pure necessity (Waleczek et al., 2018). Furthermore, internal financing can postpone the moment until the startup has to resort to outside financing, sparing the founders from having to spend too much time courting potential investors instead of taking care of the business (Markova and Petkovska-Mircevska, 2009). The initial business size as proxied by either revenues or cashflows is also found to signal favorably the growth rate of nascent businesses and entrepreneurial survival too (Cressy, 1996b). Thus, in accordance with the above stated, we hypothesize that cashflow, proxied by the revenue figure, will emit a strong signal that will be welcomed by program screeners. Therefore,

> Hypothesis 4*: A higher volume of the revenue figure will increase the likelihood of being accepted into an accelerator.*

2.3.2 Debt

Debt in start-ups is well documented in the literature. Small firm financing does not necessarily have to be based on "relationship lending" (Beck et al., 2011), and formal debt can even be found in the pre-revenue stage (Ibrahim, 2010). External debt signals positively the firm through the reliability of the expected cashflow stream (Ross, 1977). It tightens the company narrowing the management's leeway for discretionary expenditure (Jensen, 1986). Formal Debt may also accelerate the startup founding process, whether this results in success or ends up in complete failure (Hechavarria et al., 2016). The performance of leveraged startups has proved to be better than that of their unleveraged counterparts (Reynolds, 2011; Cole and Sokolyk, 2013) increasing both their growth and survival rates (La Rocca et al., 2009; Hechavarria et al., 2016). Accordingly, accelerators may endorse the screening criteria performed by institutional lenders, particularly banks, because in addition to poring over the financial statements of the applicants thoroughly for assessing their ability for servicing the debt, those procedures seem to be standardized, which could imply an industry consensus when it comes to the management of risk exposure. It wouldn't be use looking for another bank after having obtained a point-blank refusal (Mason and Stark, 2004). Accelerators may also weigh positively leveraged startups because a lower dilution of ownership of their portfolio companies may predispose founders more favorably through a higher valuation when negotiating follow-on equity investment (Ibrahim, 2010) increasing their exit rates.

Informal debt, i.e., loans taken out from the founders' family and friends, along with formal debt sourced through the pledging of the founders' own assets or from their credit cards, is also present in the sample. Thus, the finances of the firm and the finances of the entrepreneurs can frequently be intertwined causing the dividing line between formal and informal borrowing blur, especially in small businesses (Berger and Udell, 1998; Kim et al., 2006). Further, it is sometimes the presence of that type of mixed responsibilities what can explain the puzzle of formal debt in nascent ventures even in the pre-revenue stage (Wright, 2017). Although the literature is less overwhelming with respect to the advantages of either informal debt or personal collateralization, it has also been found to have positive effects, particularly on survival rates (Astebro and Bernhardt, 2003). Additionally, monies from the founder itself or from its close environment signal favorably the business through their message of strong commitment enhancing the prospects of the venture (Conti et al., 2013). Therefore, and according with the above discussed.

Hypothesis 5a: *The presence of formal debt, particularly from banks, will have a noticeable and positive effect on the likelihood of being accepted by an accelerator.*

Hypothesis 5b: *The presence of informal debt will also have a positive effect on the likelihood of being accepted by an accelerator.*

2.3.3 Equity

Common wisdom may suggest that start-ups which already sourced either angel or venture capital financing, or funds from another external equity investor, would not be interested in participating in a program, reflection that could also be extended to outside debt, but the empirical evidence registered in our sample points to the opposite direction. Roughly, one fifth of the firms that applied to an accelerator had already obtained outside equity, featuring angel investors, who ranked first, followed by other accelerator programs, and venture capitalists, who ranked third, whereas the percentage of candidates that had taken out outside debt amounted to almost 15%. Be that as it may, the fact is that the presence of certain equity investors on the balance sheet may signal applicants significantly and differently too. If external debt signals positively, and above all, the dependability of the cashflows, the ability of the applicant for servicing the debt, the signals radiated by distinct outside equity suppliers on board may help unveil disparate start-up qualities.

Much has been said about angel investors but perhaps the only assertion possible is that there is no such thing as a standardized angel investment procedure. Moreover, angels may behave quite differently when investing as lone individuals or when joining other angels forming groups. Lone angels enjoy a great deal of discretion. They normally invest in any type of businesses (DeGennaro, 2010) including firms where they might have a personal interest

(Fisher et al., 2017) and their approach may have subtle differences depending on their experience. Seasoned angels would care more about investor fit, whereas debutants and novice angels could spend more time assessing the prospects of the target deal. However, heuristics plays an important role in their decision-making regardless of their seniority (Harrison et al., 2015). Consequently, the main concern of angels seems to be agency risk rather than the performance risk of the business (Harrison and Mason, 2017). Nevertheless, angels, in addition to the personal utility that may derive from meeting entrepreneurs and the thrills of confronting the harshness of market competition, do seek a commensurate return in exchange for the risk borne from the businesses in which they invest (Shane, 2005; Goldfarb et al., 2009; Harrison et al., 2015).

On the other hand, angels increasingly organize in groups (Wiltbank and Boeker, 2007; Kerr et al., 2014) behaving much like venture capital firms do (Shane, 2008). Thus, personal considerations would be totally relegated to focus entirely on financial issues (DeGennaro, 2010; Golfarb et al. 2013). Group participation in ventures may enhance survival rates and result in more and better exits (Kerr et al., 2014). Groups tend to have larger portfolios than lone investors, with a more efficient screening and better diversified (Kerr et al., 2014) and there seems to be a direct and positive relationship between due diligence efforts and returns (Wiltbank and Boeker, 2007). Interestingly, although angel investing is intuitively associated to equity infusions, angel lending may amount to 40% of their activity, with a greater prominence of lone investors in this respect (Shane, 2009).

In contrast, venture capital decision-making is entirely driven by exit potential (Kaplan et al., 2009; Petty and Grubber, 2011; Ewens et al., 2017). The current departure of venture capital from the earliest stages of the business cycle (Hoffman and Radojevich-Kelly, 2012; Winston-Smith et al., 2013) due to both lower requirements of capital for technology-based businesses and to the inherent higher risk of fledging firms, only signals very positively the start-up (Cumming, 2008). VC involvement is an important determinant of business success (Bernstein, et al., 2016) and start-ups seem aware of that fact, which would explain their willingness to accept lower valuations in exchange for the value-added services that help them professionalize (Hsu, 2004). There seems to be a real treatment effect on the VCs' investees (Bertoni et al., 2011; Bernstein et al., 2016), who would not only cash the much-needed capital infusion but enhance team composition, improve product development, and extend their business networks (Berstein et al., 2016). Equally important is that VCs usually source their deals through peer networks being desk-rejection the most common reply to unsolicited approaches, which may lead to even finer screening (Hochberg et al., 2007). Moreover, raising funds from venture capitalists is indeed a rare event, very few applicants achieve it (Petty and Grubber, 2011; Robb and Robinson, 2014) and when they do so the business happens to be the reason for acceptance, whereas the management is often cited as the main argumentation for refusal (Petty and Grubber, 2011). Like business angels, venture capitalists also act as lenders. However, in our sample their number is much smaller.

As for inside equity, money invested from the founders' own resources or from their family and friends, reassures the confidence and the commitment of the team with respect to their own business (Prasad et al., 2000). Besides, it also helps convince outside funders because of the sharing of the risk between them and the promoters, which has the potential to further leverage in external funds because of the just mentioned risk dilution (Atherton, 2010).

Therefore, despite that the screening criteria of external equity investors is not uniform, or precisely because of so, on the one hand, and because of the positive effects of internal equity funding on the other, we formulate the hypothesis below:

Hypothesis 6a: *The presence of outside equity investors in the start-up will have a noticeable and positive impact on the likelihood of being accepted in an accelerator.*

Hypothesis 6b: *The presence of inside equity investors in the start-up will also have a positive effect on the likelihood of being accepted in an accelerator.*

2.3.4 Philanthropy

In comparison with charitable organizations, social enterprises pursue their impact goals through the deployment of normal trading activity (Shaw and Carter, 2007). However, start-ups with social intent may find access to the much-needed financial resources for developing their business plans even more difficult than their only-for-profit counterparts (Lall and Park, 2020). On the one hand, raising money from investors with purely financial interests is practically ruled out. They would fear a lack of focus from teams with dual objectives (Scarlata et al., 2016), i.e., the fulfilment of the social mission along with the maximization of the financial return. On the other, social investors may be worried about mission-drift, the gradual departure from the initial social goals to mainly economic objectives (Ebrahim et al., 2014). Empirical evidence shows, though, that social entrepreneurs could overcome those obstacles through undergoing a multi-layered process in which, in addition to commonly used business screening criteria, their commitment and probity would be further verified (Achleitner et al. 2013).

In the same vein, innovation, a business ingredient often associated with success, is frequently connected to social entrepreneurship. It is argued that while only-for-profit entrepreneurs need not necessarily be innovative, social start-ups usually achieve their goals through creative business models (Leadbeater, 1997) because opportunity-recognition is most times intertwined with past experiences and accrued knowledge, which would trigger the discovery of opportunities hidden otherwise to others with dissimilar backgrounds (Yitshaki and Kropp, 2016).

Concentrating on capital structure issues and counterintuitively, it is worth noting that social entrepreneurs do not normally mix their personal finances with the finances of the start-ups that they promote, which could suggest a lack of trust in their own intent (Shaw and Carter, 2007). However, scholarship also supports the view that mission-driven founders put at risk something of real value too, which could offset somehow that apparent lack of personal guarantees, which is their own local reputation (Achleitner et al., 2013). Interestingly, the extant literature has also recently found that there is little or no difference between the financial sources of social for-profit ventures and their only-for-profit counterparts (Guo and Peng, 2020).

Therefore, and given that the financial sustainability is essential to any venture, and that the capital structure may help the most that viability, whether that venture has a social or environmental goal, or it is only a for-profit firm, we hold that the endorsement of social investors, either lenders or equity investors, can only be beneficial to businesses, regardless of them being socially driven or not. Furthermore, scholarship has recently proved that social start-ups with philanthropic funding on their balance sheets are positively signalled in the eyes of mission-driven accelerators (Yang et al. 2020). By virtue of which,

Hypothesis 7: *The presence of outside social investors on the capital structure of applicants will cause a significant a positive impact on the likelihood of being accepted into an accelerator.*

Table 2 depicts a summary of the hypotheses for the dimensions considered.

Table 2. Hypotheses summary

Dimensions		**Hypotheses**
Human Capital	**Higher Education**	**H1**: The effect of higher education within a team will increase the likelihood of being accepted into an accelerator
	Managerial Experience	**H2**: The effect of managerial experience within teams will have a positive impact on the likelihood of being accepted into an accelerator
	Founding Experience	**H3**: The effect of prior founding experience within teams will have a negative impact on the likelihood of being accepted into an accelerator
Capital Structure	**Internal Financing**	**H4**: A higher volume of the revenue figure will increase the likelihood of being accepted into an accelerator
	Debt	**H5a**: The presence of formal debt, particularly from banks, will have a noticeable and positive effect on the likelihood of being accepted by an accelerator **H5b**: The presence of informal debt will also have a positive effect on the likelihood of being accepted by an accelerator
	Equity	**H6a**: The presence of outside equity investors in the start-up will have a noticeable and positive impact on the likelihood of being accepted in an accelerator **H6b**: The presence of inside equity investors in the start-up will also have a positive effect on the likelihood of being accepted in an accelerator
	Philanthropy	**H7**: The presence of outside social investors on the capital structure of applicants will cause a significant a positive impact on the likelihood of being accepted into an accelerator

3. Methodological Approach

3.1 Sample and Data

The last version of the 2020 GALI Database from Emory University, downloaded on 2nd March 2022, features 408 accelerators, split into 168 impact-driven programs and 157 for-profit accelerators. The remaining 83 accelerators with no information about their orientation were dismissed. The geographical spread of the programs is as follows: 112 are based in Latin America and Caribbean, 108 in North America, 31 in South Asia, 60 in Africa, and 26 in Europe, Australia, and the Middle East.

As in the database the information on the personal characteristics of team members is restricted to just three people, all the analyses included in the present work are restricted to teams of that size at most. Therefore, after adjustments, our total team count amounts to 16,426 start-ups: 4,359 solo entrepreneurs, 6,539 two-person teams, and 5,528 three-founder firms out of 23,365 startups in the database, 6,939 with more than three people per team.

Since the database is compiled from teams that applied to programs of their own accord, there will always be self-selection bias. Those ventures self-selected themselves, which means that the sample over which the accelerators performed their screening was not created haphazardly. Further, the program screeners did not choose their portfolio companies randomly either. This is the twofold perspective from which self-selection bias should be addressed (Heckman and Robb, 1985). The extent of the self-selection effect derived from the applicants' own decisions cannot be controlled for. Neither can we adjust for the same bias when produced by the program managers. That said, the start-ups included in the database are highly heterogeneous: More than 150 characteristics are used to accurately depict every venture profile. In addition to this, more than 400 programs did perform their screening over more than 23,000 firms. Therefore, the potential effects of that double self-selection can reasonably be considered negligible, a fact which is strongly backed by the recent use of the same database in the literature (Pierrakis and Owens, 2020; Lall et al., 2020; Venâncio and Jorge, 2021).

3.2 Methods

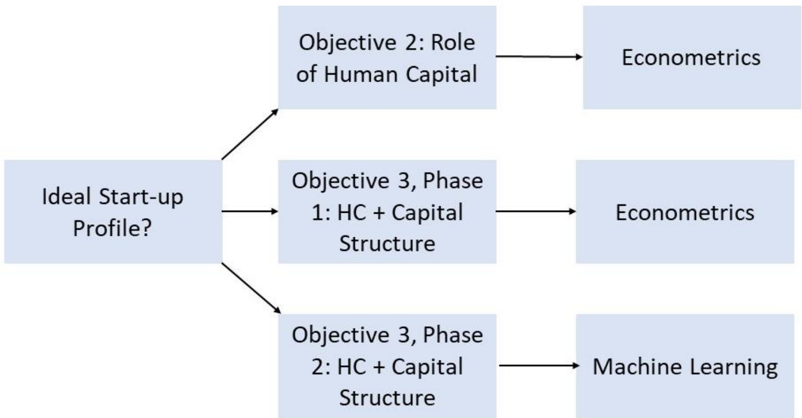
Our research problem asks whether there is an ideal start-up profile, the most sought-after venture contour, or if on the contrary there is no such thing. We do not only aim at unveiling what makes startups more appealing when it comes to raising funds in general, or what drives accelerator acceptance in particular, in the sense of what venture or team's characteristic is more important in the eyes of screeners, whether that feature is a human skill or a financing source. This has been largely discussed already in the entrepreneurial financing literature, but it still remains inconclusive.

Beginning with human capital dimensions, it is sometimes that higher education is not universally upheld (Honig, 2001; Arora and Nandkumar, 2011; Venâncio and Jorge, 2021), while some other times it is managerial experience what presents contradictory views (Peña, 2004; Samuelsson and Davidson, 2009). And the same happens to previous founding experience, which can be considered advantageous on certain occasions (Amaral et al., 2011, Ko & Mackelvie, 2017) whereas the opposite is also held on other contexts (Gottschalk et al. 2014; Nahata, 2019). Consequently, we consider worth shedding additional light on the issue through using the largest sample in the field to date. The GALI 2020 database has been used already in other investigations, but in all of them researchers have used smaller subsamples of it than that of ours, according with their focal problems (Pierrakis and Owens, 2020; Lall et al., 2020, Venâncio and Jorge, 2021). Through sourcing the largest subsample and focusing just on our three human capital dimensions, we strongly believe that valuable insight on the issue can still emerge. Therefore, in our second objective, we address exclusively the role of the three human skills of applicants to attest their relevance per se, regardless of any other considerations. What do program managers prefer, seasoned or novice entrepreneurs, PhDs or undergraduates, experienced managers, or juniors?

Subsequently, in the first phase of Objective 3, we address the human capital dimensions and the capital structure of the ventures together. Will the results of Objective 2 hold when all the different financing sources are considered? The underlying rationale of this lies in the fact that thorough capital structures and human capital characteristics have not been directly confronted yet. First, some financing sources have sometimes been used as mere controls for human capital dimensions (Venâncio and Jorge, 2021) or vice versa (Lall et al. 2020). Second, only some financing sources have been considered depending on the investigation problem. For instance, whether the presence of certain investors on board enhances the probability of raising follow-on funding (Ko and McKelvie, 2018; Pierrakis and Owens, 2020), the role of debt in startups (Berger and Udell, 1998; Ibrahim, 2010; Hechavarria et al., 2016), or whether which type of financing, i.e., equity or debt, is dominant in a sample of successful startups (Hogan et al., 2017) to name but a few. In light of this, we take advantage of the richness of the excellent GALI 2020 database, where the capital structure of the candidates is portrayed by 44 different magnitudes, to conduct a thorough investigation over the relative weight of human skills and financing sources when they are confronted. We anticipate relevant results, which would better clarify the comparative importance of each characteristic within the applicant firm.

However, if our investigation concluded here, our research problem would still remain unanswered. We would not know whether there is a most sought-after start-up profile. All we could know, at best, is if one feature out of the complete array of venture characteristics is more appreciated than the others. Whether the presence of one factor is positively or negatively regarded, or whether one particular element seems to be relatively more important than the rest. We would not know anything about the combined effect of all the ingredients under consideration. Thus, we need to transition from Econometrics to other methods which enable us to overcome the shortages of the former. Econometrics can rank the different components of a set, and it can also register their statistical significance. On the contrary, it cannot depict properly the true interactions among them. We need a holistic approach. Simply put, a start-up is not the mere addition of all its constituents. It is something different precisely because of the combined effect of those factors. In consequence, through the use of Big Data techniques, particularly, Machine Learning algorithms, we intend to uncover what the ideal start-up profile is. This is where the second phase of objective 3 culminates. Figure 1 below depicts the different research methods used in our investigation.

Figure 1. Research methods



3.3 Variables

The chosen dependent variable is a dichotomous one that features ventures that applied to, were accepted into, and participated in a program. It registers the value of 1 when a start-up team has been effectively accepted and has also participated in a program and the value of 0 otherwise.

Concerning the human capital dimensions, i.e., the education background, senior managerial experience, and founding experience, we use three different variable sets as proxies for each subdimension into which the main categories are split, for enhancing robustness. The first set is meant to higher education. Whether startups have got members possessing higher education in general, a master's degree, or a PhD, is tested through three binary variables, which register, respectively, the value of 1 when at least one member of the team meets the condition and 0 otherwise. Additionally, two more education variables have been devised. The first one measures the cumulative effect of education in teams. That is, the sum of the schooling years from 0, no schooling whatsoever, to 20 years, possessing a PhD, per each founder in the venture. The second one measures the relative weight of the overall education endowment in the startup: it is the result of dividing the total number of schooling years per team by the number of founders in the focal start-up.

Senior managerial experience shapes the second variable set and although the database registers the existence of that attribute across four different types of organizations, namely, for-profit, not-for-profit, governmental bodies, and other, this division has been reorganized into just two separate categories for clarification purposes, to wit, experience in for-profit ventures and experience in all the other types of organizations. Likewise, we consider only CEO and senior management appointments for the requirement to be met out of the four professional categories offered in the raw data. The first variable of this set is dichotomous and has been devised for registering whether any member in the team had held senior positions in the past in all type of organizations, whether for-profit or of any other classes. The variable works as mentioned before, it yields the value of 1 when the condition is met by at least one member of the team, 0 otherwise. In turn, two variables more have been constructed for further exploring the skill: a dichotomous variable registering managerial experience in only for-profit ventures, and a last one which captures when it is the majority of members within the team who possess the quality. Finally, we remove the seniority constraint for reporting whether plain work experience may signal the quality of the team. For doing so, we use a continuous variable which captures the total number of years of business experience per team.

Last, the third set of variables is meant to previous founding experience. The main variable used is a continuous one that registers the sum of the total number of firms previously founded by any team member regardless of the type of organization, whether that formerly founded venture had been for-profit, non-profit, or another type of institution. Moreover, the founding experience is further explored through three additional variables, which register the sum of only for-profit companies, the sum of any other type of organizations, and the ratio between the overall founding experience in the startup and the entrepreneur count in that same team, respectively.

With respect to the capital structure classes, we use the raw characteristics featured in the GALI database and categorize them into the same four dimensions discussed in the earlier literature review, namely, internal financing, debt, equity, and philanthropy. For depicting the financing mixture of applicants, the Emory database includes 17 types of equity investors, 15 sorts of debt suppliers, and the philanthropy count amounts to 10 different sources. All those sources are proxied through dichotomous variables which simply register the presence of the focal funding source on the balance sheet. On the contrary, the 2 variables meant to the revenue stream, both revenues since foundation and in the last year prior to application, are continuous and capture the total amount, respectively.

We also use gender, founder age, firm age, region, and sector controls. When controlling for the presence of women within teams, we use a variable set too. The main variable is a continuous one, which is the sum of female members in the firm. The first auxiliar variable is dichotomous and only reflects the mere presence of women in the team. Subsequently, the second ancillary variable displays whether women are the majority. Despite that gender is not one of our focal explanatory human characteristics, we believe worth exploring thoroughly the attribute because of the controversial attitude of fund suppliers with respect to this gender (Rahman and Zbrankova, 2019). When we deal with the age of the founders, we use a continuous variable, which is the ratio of the sum of the age of all members divided by the founder count. The age of the startups is controlled too through a continuous variable which registers the number of years elapsed since the foundation of the firm until the application date. When controlling for the region where the headquarters of the start-up is based, we use the 2021 World Bank Country Classifications by income, which splits the world economy into four different areas according with the income per capita of their inhabitants.

When activity sectors are addressed, the original 16 database sector count has been replaced by an adapted version of The Global Industry Classification Standard, GICS. Subsequently, the 11 sectors included in the latter have been summarized into seven sectors according to their affinities: energy, raw materials, and industrial; consumer staples and consumer discretionary; healthcare; information technologies and communication services; real estate and infrastructure; financial services; and other. We believe this may provide a clearer picture for our purposes.

Despite that our analyses are on teams of maximum three people, we also control for team size. We use a continuous variable that registers the sum of team members. Other additional controls are prior participation in another accelerator program, whether the business model of the applicant is invention-based, whether the start-up has social or environmental goals, whether the candidate is a for-profit venture or another type of organization, and whether the start-up has intent to achieve a certain profit percentage.

In this part of our study, all the analyses have been conducted using the latest version of the Stata statistical package, StataSE 17 (64-bit). Tables 3 to 13 show the variable set and the main descriptive statistics for the variables of interest.

Table 3. Human Capital dimensions and their variable set

Dimensions of Human Capital	Subdimensions	Variables
Educational Background	Presence of graduates in the team	Higher Education
	Presence of postgraduates in the team	Postgraduate
	Presence of PhDs in the team	PhD
	Total number of schooling years per team	Schooling Years
	Total number of schooling years / team count	Ratio Education
Managerial Experience	Presence of managerial experience in the team	Managerial Exp.
	Managerial experience in only for-profit organizations	Manag. Exp. F-p
	When there is the majority who have managerial experience	Man. Exp. Major.
	Business experience in general, regardless of the seniority	Work Experience
Founding Experience	Total number of start-ups previously founded in the team	Founding Exp.
	Total number of start-ups previously founded in the team, only for-profits	Founding Exp. F-p
	Total number of start-ups previously founded in the team, except for-profits	Founding Exp. Other
	Total number of previously founded start-ups per team / team count	Ratio Found. Exp.

Table 4. Capital Structure. Debt financing subdimensions and variables

Debt Variables	Subdimensions
Family	Debt invested in the start-up by the family of the founders
Friends & Family	Debt invested in the start-up by friends & family of the founders
Employees Not Owners	Debt invested by start-up employees who are not owners
Other Individuals	Debt invested in the start-up by other individuals
Banks	Debt invested in the start-up by banks
Non-Bank Fin. Instit.	Debt invested in the start-up by other financial institutions
Angel Investors	Debt invested in the start-up by business angels
Venture Capitalists	Debt invested in the start-up by venture capital firms
Accelerators	Debt previously invested in the start-up by other accelerator programs
Companies	Debt invested in the start-up by non-financial firms
Governments	Debt invested in the start-up by governmental bodies or agencies
Business Plan Compet.	Debt sourced through business plan competitions
Crowdfunding	Debt sourced through crowdfunding platforms
Non-profit Organizat.	Debt sourced from philanthropic organizations
Other Sources	Debt sourced from Other Sources

Table 5. Capital Structure. Equity financing dimensions and variables

Debt Variables	Subdimensions
Spouses	Equity invested in the start-up by the spouses of the founders
Parents	Equity invested in the start-up by the parents of the founders
Friends & Family	Equity invested in the start-up by friends & family of the founders
Employees Not Owners	Equity invested by start-up employees who are not owners
Other Individuals	Equity invested in the start-up by other individuals
Banks	Equity invested in the start-up by banks
Non-Bank Fin. Instit.	Equity invested i n the start-up by other financial institutions
Angel Investors	Equity invested in the start-up by business angels
Venture Capitalists	Equity invested in the start-up by venture capital firms
Accelerators	Equity previously invested in the start-up by other accelerator programs
Companies	Equity invested in the start-up by non-financial firms
Governments	Equity invested in the start-up by governmental bodies and agencies
Business Plan Compet.	Equity raised by the start-up in business plan competitions
Crowdfunding	Equity raised by the start-up through crowdfunding platforms
Non-profit Organizat.	Equity invested in the start-up by philanthropic organizations
Other Sources	Equity invested in the start-up by other than the above sources
Unknown Sources	Equity invested in the start-up whose origin is unknown

Table 6. Capital Structure. Philanthropic financing subdimensions and variables

Debt Variables	Subdimensions
Friends & Family	Philanthropy sourced from friends & family of the founders
Employees Not Owners	Philanthropy sourced from employees who ae not owners
Other Individuals	Philanthropy sourced from other individuals
Accelerators	Philanthropy previously sourced from other accelerator programs
Companies	Philanthropy sourced from non-financial firms
Governments	Philanthropy sourced from governmental bodies and agencies
Business Plan Comp.	Philanthropy sourced from business plan competitions
Crowdfunding	Philanthropy sourced from crowdfunding platforms
Non-profit Organizat.	Philanthropy sourced from philanthropic organizations
Other Sources	Philanthropy sourced from other sources

Table 7. Descriptive statistics for the endogenous variable

	Mean	SD	p50	Min	Max	Obs.
Participated	0.170	0.376	0.0	0.0	1.0	16,426

Table 8. Descriptive statistics for the human capital variables

	Mean	SD	p50	Min	Max	Obs.
Higher Education	0.878	0.327	1.0	0.0	1.0	15,178
Postgraduates	0.415	0.493	0.0	0.0	1.0	15,178
PhDs	0.064	0.244	0.0	0.0	1.0	15,178
Schooling Years	31.331	12.145	31.0	0.0	60.0	15,178
Ratio Education	15.211	1.904	15.0	0.0	20.0	15,178
Managerial Experience	1.147	0.962	1.0	0.0	3.0	13,018
Manag. Exp. Only F-P	0.740	0.873	1.0	0.0	3.0	13,010
Man. Exp. Majority	0.476	0.499	0.0	0.0	1.0	13,018
Work Experience	6.176	5.021	5.0	0.0	28.3	16,426
Founding Experience	1.964	2.584	1.0	0.0	12.0	16,426
Founding Exp. Only F-P	1.484	2.125	1.0	0.0	10.0	16,426
Founding Exp. Other	0.472	0.991	0.0	0.0	5.0	16,426
Ratio Found. Exper.	0.963	1.231	0.5	0.0	11.0	16,426

Table 9. Descriptive statistics for internal financing variables

	Mean	SD	p50	Min	Max	Obs.
Revenues Last Year	54,937	196,190	0.0	0.0	1,500,000	16,426
Revenues Since Found.	146,503	607,181	332.5	0.0	5,000,000	16,426

Table 10. Descriptive statistics for the debt investor variables.

	Mean	SD	p50	Min	Max	Obs.
Debt						
Family	0.010	0.098	0.0	0.0	1.0	16,426
Friends & Family	0.041	0.199	0.0	0.0	1.0	16,426
Employ. not Owners	0.002	0.045	0.0	0.0	1.0	16,426
Other Individuals	0.017	0.128	0.0	0.0	1.0	16,426
Banks	0.048	0.213	0.0	0.0	1.0	16,426
Non-Bank Fin. Instit.	0.018	0.131	0.0	0.0	1.0	16,426
Angel Investors	0.026	0.159	0.0	0.0	1.0	16,426
Venture Capitalists	0.009	0.094	0.0	0.0	1.0	16,426
Accelerators	0.010	0.098	0.0	0.0	1.0	16,426
Companies	0.009	0.095	0.0	0.0	1.0	16,426
Governments	0.011	0.106	0.0	0.0	1.0	16,426
Business Plan Compet.	0.005	0.070	0.0	0.0	1.0	16,426
Crowdfunding	0.003	0.058	0.0	0.0	1.0	16,426
Non-profit Organizat.	0.007	0.085	0.0	0.0	1.0	16,426
Other Sources	0.024	0.153	0.0	0.0	1.0	16,426

Table 11. Descriptive statistics for equity investor variables

	Mean	SD	p50	Min	Max	Obs.
Equity						
Spouses	0.005	0.070	0.0	0.0	1.0	16,426
Parents	0.008	0.091	0.0	0.0	1.0	16,426
Friends & Family	0.056	0.230	0.0	0.0	1.0	16,426
Employ. not Owners	0.003	0.053	0.0	0.0	1.0	16,426
Other Individuals	0.014	0.119	0.0	0.0	1.0	16,426
Banks	0.010	0.100	0.0	0.0	1.0	16,426
Non-Bank Fin. Instit.	0.006	0.077	0.0	0.0	1.0	16,426
Angel Investors	0.076	0.266	0.0	0.0	1.0	16,426
Venture Capitalists	0.032	0.177	0.0	0.0	1.0	16,426
Accelerators	0.038	0.192	0.0	0.0	1.0	16,426
Companies	0.014	0.118	0.0	0.0	1.0	16,426
Governments	0.016	0.126	0.0	0.0	1.0	16,426
Business Plan Comp.	0.011	0.103	0.0	0.0	1.0	16,426
Crowdfunding	0.005	0.073	0.0	0.0	1.0	16,426
Non-profit Organizat.	0.010	0.099	0.0	0.0	1.0	16,426
Other Sources	0.034	0.101	0.0	0.0	1.0	16,426
Unknown Source	0.017	0.131	0.0	0.0	1.0	16,426

Table 12. Descriptive statistics for philanthropic investor variables

	Mean	SD	p50	Min	Max	Obs.
Philanthropy						
Friends & Family	0.077	0.267	0.0	0.0	1.0	16,426
Employ. not Owners	0.007	0.082	0.0	0.0	1.0	16,426
Other Individuals	0.047	0.212	0.0	0.0	1.0	16,426
Accelerators	0.075	0.263	0.0	0.0	1.0	16,426
Companies	0.045	0.205	0.0	0.0	1.0	16,426
Governments	0.071	0.256	0.0	0.0	1.0	16,426
Business Plan Compet.	0.056	0.229	0.0	0.0	1.0	16,426
Crowdfunding	0.032	0.175	0.0	0.0	1.0	16,426
Non-profit Organizat.	0.102	0.303	0.0	0.0	1.0	16,426
Other Sources	0.018	0.133	0.0	0.0	1.0	16,426

Table 13. Descriptive statistics for the control variables

	Mean	**SD**	**p50**	**Min**	**Max**	**Obs.**
Sectors						
Energy/Mater.	0.134	0.340	0.0	0.0	1.0	16,319
Consumer	0.355	0.479	0.0	0.0	1.0	16,319
Health	0.107	0.301	0.0	0.0	1.0	16,319
Infotech	0.099	0.298	0.0	0.0	1.0	16,319
Real Estate	0.025	0.156	0.0	0.0	1.0	16,319
Financial	0.082	0.275	0.0	0.0	1.0	16,319
Other	0.198	0.399	0.0	0.0	1.0	16,319
Income Region						
Low	0.061	0.239	0.0	0.0	1.0	16,362
Lower-Middle	0.295	0.456	0.0	0.0	1.0	16,362
Upper-Middle	0.259	0.438	0.0	0.0	1.0	16,362
High	0.385	0.487	0.0	0.0	1.0	16,362
Other						
Av. Found. Age	34.835	9.135	33.0	18.0	70.0	16,055
Founder Count	2.071	0.772	2.0	1.0	3.0	16,426
Female Count	0.635	0.730	1.0	0.0	3.0	16,033
Target Profit	0.596	0.491	1.0	0.0	1.0	16,426
Start-up Age	3.559	3.826	2.0	1.0	77.0	15,966
Invention	0.532	0.499	1.0	0.0	1.0	16,426
Accel. Particip.	0.050	0.217	0.0	0.0	1.0	16,426
Social Motives	0.880	0.325	1.0	0.0	1.0	16,426
Legal Status	0.816	0.387	1.0	0.0	1.0	16,426

4. Econometric Analyses

In this chapter we address the role of human capital in the likelihood of entering an accelerator program, which is the second objective of our investigation, and we also analyze the role of both the human capital dimensions and of the capital structure of the applicants, which is the first phase of objective 3, according with what was stated in section 3.2 of the present work.

4.1. Econometric Model Specification

Given the qualitative nature of our dependent variable, i.e., program participation, which comes in the form of a binary response, we must choose among the econometric models available for this purpose. The Linear Probability Model could have been an option had it not been for two major drawbacks. First, the outcomes in such model can be either greater than one or lower than zero, which does not invalidate the sense of the binary response, but second and most importantly, the partial effect of the independent explanatory variables is constant (Wooldridge, 2013) which could deprive us of great insight about our research problem. Therefore, the election is reduced to two models, namely, Logit and Probit.

Both logit and probit can be derived from a latent variable model, where Y* is the unobserved, latent, variable

$$\mathbf{Y^* = \beta_0 + X\beta + \varepsilon;\ \ Y = 1\,[Y^* > 0].}$$

where the binary outcome is denoted by $Y = 1$ when $Y^* > 0$, and $Y = 0$ when $Y^* \leq 0$. Similarly, in both logit and probit ε is assumed to be independent of X, but it is only in probit where ε behaves according to the Normal Distribution, which makes it more popular in Economy-related fields. This, along with a better fit to data in most types of samples (Hahn & Soyer, 2005), makes us prefer probit for conducting our econometric analyses.

Since we test only one dependent variable against a vector of independent variables and controls, the binomial specification of the model suffices. The probit model expression is:

$$\mathbf{Y = \Phi\ (X\beta + \varepsilon)}$$

$$\mathbf{\Phi{-}1(Y) = X\beta + \varepsilon}$$

$$\mathbf{Y' = X\beta + \varepsilon}$$

where F(Y) = Φ−1(Y) is the function that links a dichotomous Y variable with a continuous Y' through the cumulative Normal Distribution. The probit model assesses the likelihood of the dependent Y variable, acceptance, and participation in a program, against a X-regressor vector, whose variables are higher education, managerial experience, and previous founding experience plus all the controls.

That said, the Logit model is also used in our tests. Particularly, we use the odd ratios obtained for further clarification of our results because they are more intuitive and can be more easily interpreted than the marginal partial effects. Therefore, we use those magnitudes for illustration purposes when appropriate.

As earlier mentioned, in this chapter, two sets of analyses are conducted. The first set comprises the probit (and logit) analyses of only the human capital variables along with controls to assess their relevance in isolation from other startup characteristics, which is the second objective of our work. Afterwards, a second set of analysis is conducted featuring also capital structure variables plus controls too, which shapes the first phase of objective 3.

4.2 Results: Human Capital Dimensions

As earlier mentioned in section 3.3, the human capital endowment of the applicants is split into three main dimensions, to wit, educational background, managerial experience, and founding experience. Subsequently, those dimensions are further categorized into subdimensions to better capture their presumed effects. The presence of graduates, postgraduates, and PhDs in the teams plus the total number of schooling years and the ratio of the total schooling years per start-up conforms the educational subdimension set. Previous senior managerial experience, managerial experience in only for-profit organizations, when it is the majority of the team who possesses the quality and, finally, work experience regardless of its seniority, shape the second subdimension block. Founding experience in general, start-up experience in only for-profit organizations, founding experience in all type of organizations except in for-profits, and the ratio between all type of organizations founded and the team count forms the third subdimension group.

Accordingly, we proceed by conducting a descriptive analysis over our complete sample, now split into two sub-samples depending on the value of the endogenous variable, for ascertaining whether there are true differences between the ventures that entered in a program and those that did not with respect to our explanatory variables. The results of the human capital subdimensions are displayed in Tables 14a and 14b below.

Table 14a. Descriptive statistics. Human capital variables of the start-ups that did not participate.

Participated = 0	**Mean**	**SD**	**p50**	**Min**	**Max**	**Obs.**
Higher Education	0.875	0.330	1.0	0.0	1.0	12,603
Postgraduates	0.410	0.492	0.0	0.0	1.0	12,603
PhDs	0.064	0.244	0.0	0.0	1.0	12,603
Schooling Years	31.215	12.148	31.0	0.0	60.0	12,603
Ratio Education	15.193	1.907	15.0	0.0	20.0	12,603
Managerial Experience	1.148	0.961	1.0	0.0	3.0	10,709
Manag. Exp. Only F-P	0.735	0.868	0.0	0.0	3.0	10,702
Manager. Exp. Majority	0.479	0.500	0.0	0.0	1.0	10,709
Work Experience	6.135	5.048	5.0	0.0	28.3	13,627
Founding Experience	1.965	2.589	1.0	0.0	12.0	13,627
Founding Exp. Only F-P	1.479	2.115	1.0	0.0	10.0	13,627
Founding Exp. Other	0.476	1.005	0.0	0.0	5.0	13,627
Ratio Found. Experience	0.971	1.246	0.5	0.0	11.0	13,627

Table 14b. Descriptive statistics. Human capital variables of the start-ups that participated.

Participated = 1	Mean	SD	p50	Min	Max	Obs.
Higher Education	0.891	0.312	1.0	0.0	1.0	2,575
Postgraduates	0.439	0.496	0.0	0.0	1.0	2,575
PhDs	0.064	0.245	0.0	0.0	1.0	2,575
Schooling Years	31.895	12.115	32.0	0.0	60.0	2,575
Ratio Education	15.296	1.887	15.0	0.0	20.0	2,575
Managerial Experience	1.144	0.970	1.0	0.0	3.0	2,309
Manag. Exp. Only F-P	0.762	0.897	1.0	0.0	3.0	2,308
Manager. Exper. Majority	0.461	0.499	0.0	0.0	1.0	2,309
Work Experience	6.379	4.881	5.3	0.0	28.3	2,799
Founding Experience	1.958	2.559	1.0	0.0	12.0	2,799
Founding Exp. Only F-P	1.503	2.170	1.0	0.0	10.0	2,799
Founding Exp. Other	0.450	0.923	0.0	0.0	5.0	2,799
Ratio Found. Experience	0.925	1.154	0.5	0.0	10.0	2,799

Since the threshold beyond which the averages of two magnitudes can be considered different can be arbitrary to some extent, we perform a t-test of equal variances (Wooldridge, 2013) on each of the former variables for further exploring their pertinence. The three null hypotheses of the t-test are meant to verify whether there is either a positive or negative true difference between the averages of the descriptive statistics according to participation or not, or if it is its absolute value that differs. If only one null can be rejected, then, the focal variable can be expected to be relevant in the subsequent econometric model. Table 15 highlights that PhDs, along with general managerial experience, managerial experience in only for-profit firms, when it is the majority of the team who has managerial experience, founding experience in general, founding experience in only for-profits, and founding experience in all type or organizations except for-profits are not expected to be pertinent. The first three columns of Table 15 register the p-value for the negative difference, the p-value for the absolute difference, and the p-value for the positive difference, respectively.

Table 15. T-tests of equal variances on the human capital variables

	Ho: diff < 0	**Ho: diff ≠ 0**	**Ho: diff > 0**	**Particip.=0**	**Particip.=1**
	Pr (T < t)	**Pr (|T|> |t|)**	**Pr (T > t)**		
Higher Education	0.0145	0.0291	0.9855	12,603	2,575
Postgraduates	0.003	0.0061	0.997	12,603	2,575
PhDs	0.4786	0.9573	0.5214	12,603	2,575
Schooling Years	0.0048	0.0096	0.9952	12,603	2,575
Ratio Education	0.0065	0.0129	0.9935	12,603	2,575
Managerial Experience	0.5742	0.8517	0.4258	10,709	2,309
Manag. Exp. Only F-P	0.0953	0.1905	0.9047	10,702	2,308
Manager. Exp. Majority	0.9442	0.1116	0.0558	10,709	2,309
Work Experience	0.0095	0.0189	0.9905	13,627	2,799
Founding Experience	0.5552	0.8895	0.4448	13,627	2,799
Founding Exp. Only F-P	0.2939	0.5877	0.7061	13,627	2,799
Founding Exp. Other	0.8965	0.2071	0.1035	13,627	2,799
Ratio Found. Experience	0.9626	0.0747	0.0374	13,627	2,799

One possible inconvenience of the test of equal variances is the assumption that the variables under scrutiny are normally distributed, which is not the case in our population. Figures 2 and 3 exhibit two examples of non-normality through the comparison between the density function of the normal distribution and the density functions of the meant variables. However, by virtue of the Central Limit Theorem and due to the large size of our sample, the underlying distribution of the means of each subsample will converge to normality rendering the outcomes depicted in the above Table 15 robust enough.

Figure 2. Comparison between the density function of the Normal distribution and the density function for the higher education subdimension when it is proxied by its binary variable.

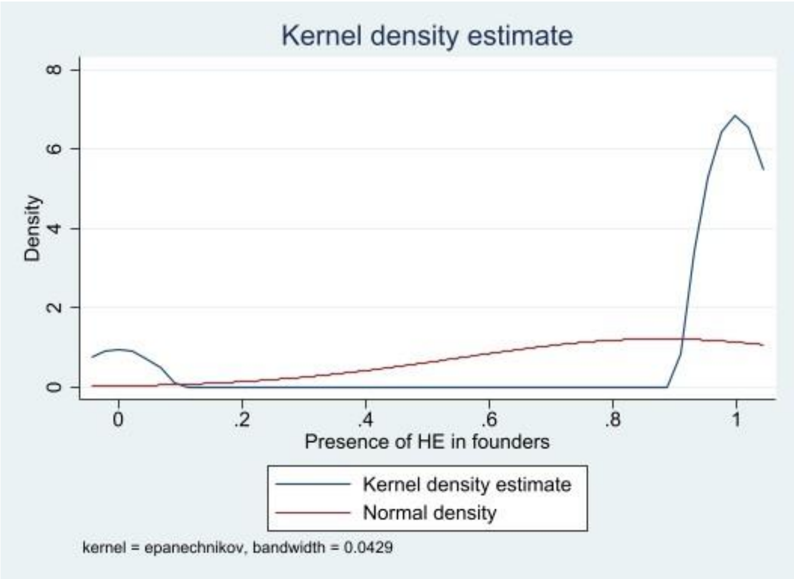
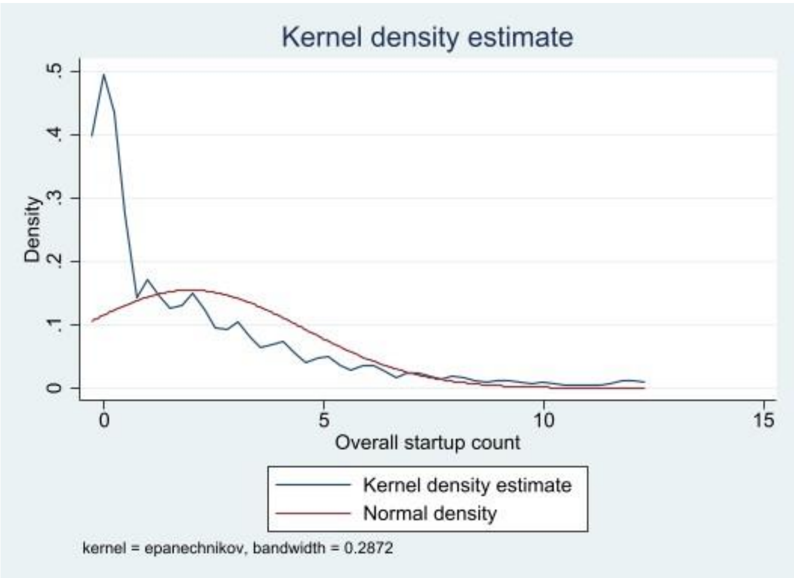


Figure 3. Comparison between the density function of the Normal distribution and the density function of founding experience when it is proxied by the continuous variable which registers the total number of start-ups founded per team



Nevertheless, we also conduct an additional analysis, which is the Mann-Whitney-Wilcoxon rank sum test (Chen et al., 2021) which is a commonly used procedure when there is no normality, the samples are very small and, consequently, the Central Limit Theorem cannot be fulfilled. The null of the rank test contends that both samples are equal, and the first column of Table 16 depicts the corresponding p-values.

Table 16. Mann-Whitney-Wilcoxon rank sum test for the human capital variables

	Prob > ǀZǀ	Particip.=0	Particip.=1
Higher Education	0.0291	12,603	2,575
Postgraduates	0.0061	12,603	2,575
PhDs	0.9573	12,603	2,575
Schooling Years	0.0059	12,603	2,575
Ratio Education	0.0044	12,603	2,575
Managerial Experience	0.7619	10,709	2,309
Manag. Exp. Only F-P	0.3794	10,702	2,308
Manager. Exp. Majority	0.1116	10,709	2,309
Work Experience	0.0005	13,627	2,799
Founding Experience	0.7531	13,627	2,799
Founding Exp. Only F-P	0.7917	13,627	2,799
Founding Exp. Other	0.9403	13,627	2,799
Ratio Found. Experience	0.6448	13,627	2,799

Accordingly, and after testing all the human capital subdimensions thoroughly, our definitive human capital model is the probit regression whose results are depicted in Table 17. In doing so we accomplish our second research objective and its associated research question, that is, *what is the role of the HC in the likelihood of being accepted in an accelerator?* The choice of this model is justified because it is the one that has presented the highest explanatory power, i.e., the best Wald Chi squared, Pr>Chi^2, and Pseudo R2 outcomes, along with the highest number of observations.

Table 17. Partial Model. Human Capital variables

	Probit Coefficient	P-Value	Marginal Effect at Means	Logit Odds Ratio
Participated				
I. Human Capital Dimensions				
Higher Education	0.0687	0.106	0.1723	1.125
Postgraduate	0.0722	0.011	0.0181	1.140
PhD	-0.045	0.407	-0.0113	0.922
Work Experience	0.0068	0.043	0.0017	1.012
Founding Exp.	-0.0055	0.296	-0.0014	0.990
II. Controls				
Sector				
Consumer	-0.0727	0.068	-0.0183	0.879
Health	-0.0128	0.801	-0.0033	0.977
Infotech	-0.1444	0.007	-0.0352	0.772
Real Estate	0.0514	0.542	0.0138	1.095
Financial	-0.0396	0.472	-0.0102	0.932
Other	-0.0029	0.948	-0.0007	0.998
Income Region				
Lower-Middle	0.1239	0.033	0.2705	1.261
Upper-Middle	0.2496	0.000	0.0582	1.566
High	0.2546	0.000	0.0596	1.581
Other				
Av. Found. Age	-0.0054	0.006	-0.0014	0.991
Founder Count	0.0184	0.302	0.0046	1.031
Female Count	0.0750	0.000	0.0188	1.144
Target Profit	0.0660	0.015	0.0166	1.124
Start-up Age	0.0229	0.000	0.0057	1.040
Invention	-0.0756	0.003	-0.0190	0.875
Accel. Particip.	0.3033	0.000	0.7611	1.693
Social Motives	-0.0260	0.558	-0.0065	0.950
Legal Status	0.1965	0.000	0.0493	1.429
Obs.	14,307			
Wald chi2(22)	194.28			
Prob > chi2	0.0000			
Pseudo R2	0.0148			

When higher education is considered as one single construct including the complete set of university degrees, it has never been significant across all tested models. In contrast, postgraduates seem to be welcome. They are significant (0.011 p-value) with a positive marginal effect of 1.81% (logit odds ratio 1.140). That is, if the characteristic increases by 1 unit, the likelihood of acceptance in a program does so by 1.81%. Put differently, when the quality is present in the team, the probability of admission rises by 14.0% (odds ratio). The PhD variable has never been significant either, though. This result was anticipated when examining the differences between the means in the two subsamples. The mean of PhDs in startups that did participate is 0.064, whereas PhDs in startups that did not participate average 0.064 (see Tables 14a and 14b, respectively). It is exactly the same figure. Additionally, the results of both the t-test of equal variances and the rank sum test pointed exactly to the same direction. When we use the other variables for testing the relevance of education, i.e., total years of schooling and the ratio between that accrued education endowment and the total entrepreneur count, results reinforce the proven value of education, albeit somewhat disappointingly. Both variables are truly significant (at 1%) although their effects are almost negligible, 0.25% and 0.5% marginal effects, respectively. In light of these results, the relevance of PhDs in teams could be reconsidered: On the one hand, if it is true that the binary PhD variable is never significant, it is no less true that PhDs might also be included in the total years of schooling and in the education ratio. On the other, the econometric analysis can only test the effect of the variable in isolation. Therefore, the presence of the highest education degree should not be dismissed straightforwardly. Our results are in line with the literature to this respect: Hsu (2007) found that PhDs were only wanted in the Internet industry but rejected in all the other sectors, whereas Ratzinger et al. (2018) found that PhDs in business were more likely to raise equity financing. In general, the above results may indicate a subtle preference for individuals possessing higher education, preferably postgraduates. Therefore, hypothesis 1 is partly supported.

Senior managerial experience has been tested through three binary variables. The first one captures the presence of senior managers in teams, and the other two register senior experience in only-for-profit organizations and when it is the majority of the team who possesses the skill, respectively. The first variable is never significant. As with the PhD variable, the means of the two subsamples are too close, 1.144 for those start-ups that joined a program, whereas startups that did not participate average 1.148. Additional confirmation is also supplied by the test of equal variances and the rank sum analysis. Similarly, the other two managerial variables are never significant. According to those results, we relax the seniority restriction and try to capture the effect of general human capital, sometimes argued to be even more important than specific experience (Bruhn et al., 2010; Stucki, 2016; Dimov, 2017), through simply the sum of the years of work experience regardless of the industry and the rank. Years of work experience happens to be a significant variable, but its effects are negligible, just a 0.17% marginal increase (1.012 odds ratio). As hypothesis 2 was strictly formulated to emerge whether senior appointments are welcome by programs, it is partly unsupported because those senior positions seem to have no connection with our accelerator universe.

As for previous founding experience, when general founding experience is verified, it is not significant (0.296 p-value). Further tests conducted for verifying whether that result could be biased due to mixing together previous experience in both for-profits and in any other types of organizations have turned the same outcome. The variable that captures only-for-profit startup experience is never significant either. Moreover, we scrutinize founding experience in only other type of institutions, to no avail. Last, when we use the variable that indicates the relative weight of the characteristic in the team, that is, the total number of previously funded ventures regardless of its type divided by the entrepreneur count, results persist stubbornly. Therefore, hypothesis 3 is partly unsupported.

The fact that the average age of the entrepreneurs who did join an accelerator is higher, 35.13 years, than the mean of those who did not, 34.78, contrasts with the minor negative marginal -0.14% effect (0.991 odds ratio) registered by the regression. It could be because both ages are at the upper limit considered optimal by some authors when it comes to entrepreneurship (Lévesque and Minniti, 2006), which would obtain further support by some anecdotal evidence on the issue (Rich, 2013). In contrast, nothing can be said about team size because the variable is not pertinent (p-value 0.302), which deprives us of knowing whether the accelerators in our sample are aligned with the positive stance of scholarship with respect to teams versus solo entrepreneurs (Cooper et al., 1998).

Women are really welcome in programs. When the total female count is registered, it yields a positive 1.88% marginal effect (1.144 odds ratio). Similarly, when they are the majority, the marginal effect is even higher, 2.63% (odds ratio 1.205), and the same occurs when only the mere female presence is registered through a dichotomous variable: a 2.86% marginal effect (1.228 odds ratio). When we shift to the industry in which the startup operates, only the information and communication technology sectors are relevant across all the other activities, and start-ups which choose those businesses pay a severe penalty for that: the variable turns a -3.52% negative marginal effect (0.772 odds ratio). On the contrary, companies are welcome regardless of the region where their headquarters are based. The marginal effects are 2.70%, 5.82%, 5.96% for the lower-middle, upper-middle, and high-income regions, respectively (1.261, 1.566, and 1.581 odds ratios).

Accelerators seem to be rather neutral with respect to the age of the firms. The cumulative variable that accrues the number of years that have elapsed since foundation until the application date turns just a 0.57% positive marginal effect (1.040 odds ratio). The profit intent is positively regarded by program managers. The start-ups that state a certain profit goal through a percentage register a 1.66% marginal effect (1.124 odds ratio). Interestingly, programs seem suspicious when presented with innovative business ideas. The characteristic turns a negative -1.90% marginal effect (0.875 odds ratio). This, along with both the irrelevance of patents on the one hand and with the negative effect of being a tech business on the other, might suggest that, in our sample, accelerators in general do not bet on innovation. On the contrary and surprisingly, previous participation in an accelerator program yields by far the highest effect across all the other variables in the analyses: an astounding 7.61% marginal effect (1.693 odds ratio). Whether start-ups are mission-driven has turned out to be irrelevant in our sample as the variable is no significant. Therefore, nothing can be said about the attitude of programs about socially or environmentally-conscious entrepreneurs, neither positive, nor negative. Last, if social or environmental goals seem to have no connection to this study, for-profit intent clearly does. Ventures that admit the pursuit of a financial profit through its legal status are welcome, they turn a 4.93% positive marginal effect (1.429 odds ratio).

4.3 Results: Human Capital Dimensions plus Capital Structure Dimensions

In this section we address research objective 3, that is the relevance of human capital when combined with capital structure. Here, we use traditional econometric techniques to investigate this matter. First, we explore where truly significant financing sources can be found out of the impressive array offered by the GALI database. We use the same procedures and tests utilized in the former section, although we only include tables for the equity sources for economy reasons. Tables 18 to 21 feature those tests.

Table 18. Descriptive statistics of the equity financing variables for firms that did not participate

Participated = 0	**Mean**	**SD**	**p50**	**Min**	**Max**	**Obs.**
Equity						
Spouses	0.005	0.072	0.000	0.000	1.000	13,627
Parents	0.008	0.091	0.000	0.000	1.000	13,627
Friends & Family	0.056	0.231	0.000	0.000	1.000	13,627
Employees not Owners	0.003	0.052	0.000	0.000	1.000	13,627
Other Individuals	0.015	0.120	0.000	0.000	1.000	13,627
Banks	0.009	0.095	0.000	0.000	1.000	13,627
Non-Bank Fin. Instit.	0.005	0.073	0.000	0.000	1.000	13,627
Angel Investors	0.069	0.254	0.000	0.000	1.000	13,627
Venture Capitalists	0.029	0.169	0.000	0.000	1.000	13,627
Accelerators	0.035	0.184	0.000	0.000	1.000	13,627
Companies	0.013	0.114	0.000	0.000	1.000	13,627
Governments	0.015	0.123	0.000	0.000	1.000	13,627
Business Plan Compet.	0.010	0.100	0.000	0.000	1.000	13,627
Crowdfunding	0.005	0.072	0.000	0.000	1.000	13,627
Nonprofit Organizat.	0.009	0.094	0.000	0.000	1.000	13,627
Other Sources	0.033	0.100	0.000	0.000	1.000	13,627
Unknown Source	0.018	0.134	0.000	0.000	1.000	13,627

Table 19. Descriptive statistics of the equity financing variables for firms that participated

Participated = 1	**Mean**	**SD**	**p50**	**Min**	**Max**	**Obs.**
Equity						
Spouses	0.004	0.060	0.000	0.000	1.000	2,799
Parents	0.008	0.090	0.000	0.000	1.000	2,799
Friends & Family	0.055	0.227	0.000	0.000	1.000	2,799
Employees not Owners	0.003	0.057	0.000	0.000	1.000	2,799
Other Individuals	0.014	0.117	0.000	0.000	1.000	2,799
Banks	0.015	0.123	0.000	0.000	1.000	2,799
Non-Bank Fin. Instit.	0.009	0.094	0.000	0.000	1.000	2,799
Angel Investors	0.110	0.313	0.000	0.000	1.000	2,799
Venture Capitalists	0.046	0.210	0.000	0.000	1.000	2,799
Accelerators	0.055	0.227	0.000	0.000	1.000	2,799
Companies	0.018	0.134	0.000	0.000	1.000	2,799
Governments	0.020	0.140	0.000	0.000	1.000	2,799
Business Plan Compet.	0.014	0.119	0.000	0.000	1.000	2,799
Crowdfunding	0.006	0.080	0.000	0.000	1.000	2,799
Non-profit Organizat.	0.015	0.122	0.000	0.000	1.000	2,799
Other Sources	0.036	0.187	0.000	0.000	1.000	2,799
Unknown Source	0.014	0.116	0.000	0.000	1.000	2,799

Table 20. T-tests of equal variances on the equity financing variables

	Ho: diff < 0	Ho: diff ≠ 0	Ho: diff > 0	Particip.=0	Particip.=1
Equity	**Pr (T < t)**	**Pr (|T|> |t|)**	**Pr (T > t)**		
Spouses	0.8789	0.2421	0.1211	13,627	2,799
Parents	0.5466	0.9067	0.4534	13,627	2,799
Friends & Family	0.6445	0.7110	0.3555	13,627	2,799
Employees not Owners	0.3242	0.6483	0.6758	13,627	2,799
Other Individuals	0.5952	0.8096	0.4048	13,627	2,799
Banks	0.0011	0.0023	0.9989	13,627	2,799
Non-Bank Fin. Instit.	0.0146	0.0293	0.9854	13,627	2,799
Angel Investors	0.0000	0.0000	1.0000	13,627	2,799
Venture Capitalists	0.0000	0.0000	1.0000	13,627	2,799
Accelerators	0.0000	0.0000	1.0000	13,627	2,799
Companies	0.0201	0.0403	0.9799	13,627	2,799
Governments	0.0424	0.0848	0.9576	13,627	2,799
Business Plan Compet.	0.0240	0.0480	0.9760	13,627	2,799
Crowdfunding	0.2115	0.4230	0.7885	13,627	2,799
Non-profit Organizat.	0.0014	0.0029	0.9986	13,627	2,799
Other Sources	0.2426	0.4853	0.7574	13,627	2,799
Unknown Source	0.9579	0.0841	0.0421	13,627	2,799

Table 21. Mann-Whitney-Wilcoxon rank sum test on the equity financing sources

Equity	Prob > |Z|	Particip.=0	Particip.=1
Spouses	0.2421	13,627	2,799
Parents	0.9067	13,627	2,799
Friends & Family	0.7110	13,627	2,799
Employees not Owners	0.6483	13,627	2,799
Other Individuals	0.8095	13,627	2,799
Banks	0.0023	13,627	2,799
Non-Bank Fin. Instit.	0.0293	13,627	2,799
Angel Investors	0.0000	13,627	2,799
Venture Capitalists	0.0000	13,627	2,799
Accelerators	0.0000	13,627	2,799
Companies	0.0403	13,627	2,799
Governments	0.0848	13,627	2,799
Business Plan Compet.	0.0480	13,627	2,799
Crowdfunding	0.4230	13,627	2,799
Nonprofit Organizat.	0.0029	13,627	2,799
Other Sources	0.4853	13,627	2,799
Unknown Source	0.0841	13,627	2,799

The t-tests and the rank sum tests in tables 22 and 23 showcase that out of the 17 equity sources 7 are clearly significant, namely, banks, non-bank financial institutions, business angels, venture capitalists, accelerators, non-financial firms, and non-profit organizations. Governments seem to be finally excluded, and equity from business plan competitions seems to be on the border of statistical relevance.

When addressing the debt sources, out of the 15 debt classes, only three seem to be not significant for the purposes of our analyses, to wit, debt from employees who have no stakes in the firms they work for, money from non-financial firms, and debt from family. With respect to this last category, it is worth noting that the GALI database features also debt from family and friends and that this category has turned out to be relevant in the t and rank tests (not shown in these pages as earlier mentioned).

Last, when it comes to philanthropy, results are more evenly distributed. Out of the 10 different classes, 4 are clearly not relevant, namely, philanthropy from friends and family (here, there no single category for just ‘family’), from other individuals, from crowdfunding, and from other sources. Philanthropic giving from employees who are not owners in their respective firms is on the boundary of relevance.

According to all the above outcomes and after conducting multiple econometric tests, we depict the results of our definitive full model in Tables 22 and 23, which features both the capital structure of start-ups plus their human capital endowment.

Table 22. Full model: human capital plus capital structure variables

	Probit Coefficient	P-Value	Marginal Effect at Means	Logit Odds Ratio
Participated				
I. Human Capital Dimensions				
Higher Education	0.0576	0.172	0.1434	1.101
Postgraduate	0.0428	0.138	0.0107	1.083
PhD	-0.7121	0.196	-0.0177	0.879
Work Experience	0.0080	0.015	0.0020	1.014
Founding Exp.	-0.0301	0.005	-0.0075	0.947
II. Capital Structure Variables				
Debt from Banks	0.2336	0.000	0.0581	1.493
Debt from Angels	0.2905	0.000	0.0722	1.644
Debt from Accel.	0.2602	0.021	0.0647	1.558
Equity from Angels	0.2583	0.000	0.0642	1.562
Equity from Govern.	-0.2136	0.036	-0.0531	0.694
Equity from VC	0.1592	0.021	0.0396	1.320
Equity from Accel.	0.1423	0.029	0.0354	1.279
Equity from F&F	-0.1713	0.003	-0.0426	0.737
Philan. from Gov	0.1087	0.023	0.0270	1.209
Philan. from Non-prof.	0.1589	0.000	0.0395	1.332
II. Controls				
Sector				
Consumer	-0.0770	0.055	-0.0194	0.874
Health	-0.0249	0.629	-0.0064	0.957
Infotech	-0.1389	0.012	-0.3388	0.783
Real Estate	0.0520	0.531	0.0139	1.106
Financial	-0.0908	0.106	-0.0227	0.856
Other	0.0015	0.972	0.0004	1.011
Income Region				
Lower-Middle	0.1218	0.037	0.0269	1.257
Upper-Middle	0.2402	0.000	0.0564	1.542
High	0.2074	0.000	0.0479	1.454
Other				
Av. Found. Age	-0.0049	0.013	-0.0012	0.992
Female Count	0.0823	0.000	0.0205	1.157
Target Profit	0.0591	0.029	0.0015	1.106
Start-up Age	0.0168	0.000	0.0042	1.030
Invention	-0.0924	0.000	-0.0230	0.847
Accel. Particip.	0.3096	0.000	0.0770	1.711
Social Motives	-0.0441	0.320	-0.0110	0.922
Legal Status	0.1978	0.000	0.0490	1.442

Table 23. Full model regression descriptive statistics

Obs.	14,307
Wald chi2(22)	331.25
Prob > chi2	0.0000
Pseudo R2	0.0256

The explanatory power and the fit of the full model (human capital characteristics plus capital structure elements) are better than those of the partial one (only human capital features), as testified by the regression output and further supported by the Akaike criterion (Lall et al. 2020). Hence, let us compare first whether the introduction of capital structure characteristics modify previous human capital outcomes, and then let us direct our attention to the consequences caused by those financial factors themselves.

The first noticeable correction is that postgraduates are now irrelevant and higher education in general and PhDs continue to be so as well. Moreover, when we replace those variables by either the overall schooling years or the education ratio, results are still the same. Therefore, the introduction of financial variables seems to render education inconsequential. Thereupon, hypothesis 1 is definitively unsupported.

When focusing on managerial skill, we have implemented the whole variable set again not to miss any possible reaction of the data to the introduction of the new factors. Results are exactly the same, and all the proxies for seniority are not significant. In contrast, work experience remains virtually unaltered. Therefore, hypothesis 2 stays as when only human factors were featured, partly unsupported.

Let us now turn to founding experience. When we use the total number of start-ups founded regardless of its type, the variable is not significant, and we obtain the same outcome when that variable is replaced by the one that registers experience in only for-profits. However, when the skill is proxied by experience in any type of organizations except for-profits, it becomes relevant (significant at 5%, -0.66% marginal effect, 0.952 odds ratio). Furthermore, when we use the ratio between any type of ventures (both for-profits plus any other classes) and the founder count, it is significant too, now at 1%, with a -0.75% marginal effect, and a 0.947 odds ratio. Thus, accelerators may dislike teams with too much start-up experience, especially is that experience is tinged with a non-profit background, by virtue of which, hypothesis 3 transitions from partly unsupported to fully supported.

We shall now proceed to examine the capital structure elements. First, let us consider internal financing proxied by the revenue figure, both since the venture's inception and also only in the last year. Results are clear in all tested models and render the two magnitudes irrelevant since they are never statistically significant. Ergo, as nothing can be said about the presumed role of internal financing, neither positive nor negative, hypothesis 4 is partly unsupported.

When we direct our attention to debt, it clearly transpires that no inside borrowing is relevant. However, external debt sources play an important and decidedly positive role. When it is banks who back the start-up, the marginal effect is 5.81% (1.493 odds ratio). Similarly, angel debt financing is much appreciated (7.22% and 1.644, respectively). Last, ventures that managed to borrow money from accelerators are also signaled very favorably (6.47% and 1.558, respectively). Accordingly, hypothesis 5a is clearly supported, whereas hypothesis 5b is partly unsupported.

In the same vein, equity funders on the balance sheet, either internal or external, gives us great insight. Accelerators seem to punish severely start-ups with financing from relatives and friends. A negative -4.26% marginal effect (0.737 odds ratio) should make entrepreneurs consider application if they cannot present additional arguments. Moreover, no other inside equity source is relevant. Consequently, hypothesis 6b is unsupported. On the contrary, outside equity is mostly and definitely welcome. When the firm has raised equity from angel investors the acceptance premium translates into a 6.42% marginal effect (1.562 odds ratio), which corroborates the importance that accelerators attach to the signals emitted by angels on board. The same happens when it is venture capitalists who back the startup (3.96% marginal effect, 1.320 odds ratio), and when accelerators themselves contribute their monies, 3.54% and 1.279. Unfortunately, we cannot infer from the database's raw data whether those accelerator stakes in applicants with previous experience just mean the usually modest stipend that programs pay to their portfolio companies or further equity investment in proven winners when harvest time has arrived. The only negative note is equity from governments, which seems to harm seriously the prospects of the firm. A negative -5.31% marginal effect (a really low 0.694 odds ratio). Hence, we consider hypothesis 6a fairly supported.

As for the effect of philanthropic financing, only two sources may cause an impact on the likelihood of entering a program. The greatest effect comes from non-profit organizations (3.95% marginal effect and 1.332 odds ratio) followed by governmental support (2.70% and 1.209, respectively). Here, we find what might seem a contradiction. When investment by governments is conveyed through equity it appears to curtail severely the odds of being accepted, whereas when that support is conducted by philanthropic giving the effect is just the opposite. Our conjecture to this puzzle is that perhaps governmental equity may also entail seats on the board, which could mean the introduction of bureaucratic inefficiencies in the daily management of the backed firm due to a less agile decision-making process, something which could be negatively regarded by accelerators. Alternatively, it might also be that accelerators relate governmental equity support with just pure subsidizing, whose presence could mask a certain inability for self-sustainability, consequently spoiling other start-up features. On the other hand, philanthropic infusions may not necessarily be accompanied by such control constraints, and as earlier discussed in the literature review, that altruistic support might well have been achieved after successfully passing strenuous screenings. In consequence, hypothesis 7 is fully supported. See Table 24 for a hypothesis summary.

Last, when the control variables are addressed, the total founder count still is not significant as whether the applicants are socially or environmentally driven. All the other controls register the same results as when tested in the partial model.

Table 24. Full model's hypothesis validation

<table>
<tr><th colspan="2">Dimension</th><th>Hypothesis Validation</th></tr>
<tr><td rowspan="3">Human Capital</td><td>Higher Education</td><td>H1: Unsupported</td></tr>
<tr><td>Managerial Experience</td><td>H2: Partly Unsupported</td></tr>
<tr><td>Founding Experience</td><td>H3: Supported</td></tr>
<tr><td rowspan="4">Capital Structure</td><td>Internal Financing</td><td>H4: Partly Unsupported</td></tr>
<tr><td>Debt</td><td>H5a: Supported
H5b: Partly Unsupported</td></tr>
<tr><td>Equity</td><td>H6a: Supported
H6b: Unsupported</td></tr>
<tr><td>Philanthropy</td><td>H7: Supported</td></tr>
</table>

So far, Econometrics has helped us understand that accelerators value positively but not enthusiastically work experience. They seem to have a slight aversion to entrepreneurs with too much founding experience, especially if that experience stems from non-profit organizations. Indeed, they welcome outside financing sources with the only exception of governmental stakes. Debt is much liked, and business angels seem to be their preferred endorsers. They also appear to be reluctant to bet on innovative ideas. And finally, previous participation in other programs is much appreciated.

5. Big Data. The Pursuit of the Ideal Startup

The characteristics listed at the end of the former section give us great insight into the preferences of accelerator managers, what they might or might not like. Presumably, the union of two or more positively regarded factors would yield a positive outcome too. However, Econometrics cannot tell us what the best combination of those factors is. Will a three positive-characteristic set necessarily be more esteemed than a two-factor one? May a factor change its sign, i.e., from negatively to positively considered (or vice versa) when combined? May apparently dismissed factors regain acceptance? These are the type of questions that we intend to answer in the second phase of our third objective through using Big Data techniques, particularly, Machine Learning. We first use Decision Trees and then move on to Association Rules.

5.1 Decision-Making and Artificial Intelligence

We already mentioned at the beginning of this work the technological and digital revolutions in which we are living as one of the main drivers of the spawning of the startup phenomenon, and it would not be exaggerated to say that one of the spearheads of those revolutions, i.e., Artificial Intelligence, already exerts a strong command over an ever-increasing number of fields in which proper decision-making can make a difference. Entrepreneurship and Finance could not remain alien to that pervasive influence and Big Data techniques are commonly used in their realm (Ahmad, et al. 2021).

Throughout these pages we have been highlighting the difficulty of making decisions in the entrepreneurial arena, especially when valuing startups. The usual scarcity of information, i.e., track record and audited financial reports, makes it really difficult in comparison with already well-established mature companies. And we have been reviewing too different signals, from firm characteristics to gut feeling, which could help amateur and institutional investors better select their portfolio companies. The point is that due precisely to the often extreme degree of informational opacity, those signals might not suffice and may force investors to put too much weight of personal judgement on the scales plates of their resolutions. Moreover, the already cited tremendous reduction in experimentation costs for launching new businesses has its own translation here too. Otherwise stated, there is a need for more data-driven analysis which would surely imply more precise and cost-effective decision-making.

Artificial Intelligence in general, and Machine Learning in particular, may help make better decisions through widening the clearance for forecast at the expense of curtailing the scope for personal judgement (Ferrati and Muffato, 2021). Better predictions through Machine Learning may render decisions less risky (Golej, 2020) on good understanding that it cannot establish causal relationships (Agrawal et al. 2019). Rather, it can disclose invaluable information entangled in past data which would have gone unnoticed otherwise. Needless to say, Artificial Intelligence should not and cannot replace neither accrued experience, nor common sense but thanks to its degree of development and easy access to many of its techniques, it would be reckless or frivolous, or both, not to use it.

5.2 Decision Trees, Supervised and Unsupervised Learning

Machine learning models are implemented in a variety of settings (Miranda et al., 2019; Sabahi and Parast, 2020; Fragkiskos et al., 2022) and the deployment of such models can be done through supervised or unsupervised learning. At the core of Machine Learning are mathematical algorithms, which are expected to discover output, i.e., magnitudes, patterns, etc., out of past data and that data will be used for making decisions. That output can be in the form of classifications, regressions, or associations, mainly. A manifestation of the first can be the classification of an object on instance of one attribute, be suitable or not suitable for a purpose. An example of a regression can be forecast on the sales figure of a product reliant on the input data. Last, an instance of an association can be inferring a rule that registers how often something occurs when something else also happens.

Unsupervised learning means that algorithms learn by themselves through analyzing the raw input with which they have been fed. On the contrary, supervised learning implies human oversight. Depending on the object the investigation and the method chosen, the implied algorithms may need some previous training for serving their purposes. That human supervision means labelling the data, what the researcher wants to find, and training previously the mathematical instruction set for getting more adjusted results.

In our study we use both approaches, supervised and unsupervised learning. Decision Trees, DT, is a clear example of supervised learning because the algorithm is preliminarily trained for better finding the different paths that may lead to the goal of the investigation. The raw data supplied by the GALI database, further recoded in our research, does not imply supervision in itself. Rather, that supervision is exerted when the algorithm is told what should be found and trained in consequence: Participation in a program.

5.2.1 Model Specification

Most of the labelling of our data responds to simple binary decisions: whether a startup has been admitted and has participated in an accelerator program or not, whether their members have got higher education, whether the firm is endorsed by a business angel through equity investment, etc. Accordingly, we have chosen DT because it is one the most appropriate techniques for conducting those binary classifications along with the CART algorithm because it is widely supported by researchers (Xu et al., 2018; Mahesh, 2020). In fact, CART stands for Classification and Regression Tress.

A decision tree is self-explanatory as it follows a hierarchical path along which every subsequent decision has been previously conditioned by the former. The tree must have a root, its starting point, and from the root the tree grows branches downwards, which end in new nodes each. The major challenge is to identify the attribute of each node, so that the tree can continue its deployment until it stops growing. The underlying rationale of the tree construction is entropy, the concept borrowed from Physics that describes the level of disorder, uncertainty, or randomness.

The CART algorithm selects the attribute of the sample which presents the lowest entropy possible out of all the other attributes. And for doing so it uses the Gini index, also known as the Gini Impurity Index, which is the criterion that fits best our study because it allows simpler partitions than other indices such as Information Gain or Chi-Squared (Tangirala, 2020). The Gini Index formula is shown below:

$$Gini\ Index = 1 - \sum_{\mathrm{i}=1}^{\mathrm{i}=n} [\mathrm{Pi}]\text{^}2$$

The formula registers the probability that certain attribute has been chosen wrongly when selected randomly. It ranges from 0 to 1. When the index equals 0, it means that the attribute or category is pure, there is no entropy. Put differently, if the entropy of a node is 0, all members in that node have the quality and there is no other member in the node that does not have it. On the contrary, when the index = 1, the attribute is randomly distributed in the node across all the observations. Finally, when the index scores 0.5 it means that the attribute is evenly distributed.

By convention, when the answer to one node is positive, a new branch will grow to the left, whereas when the answer is in the negative, the branch will grow to the right. The tree stops growing either when it finds a pure node, no entropy, or when a limit has been previously set. The three may show two or more ending nodes which are equal, and shorter branches can also be grown. For example, a three-node branch within a ten-level tree. In our work we have set a six-level limit to allow for enough space for accommodating the three human capital dimensions plus three capital structure elements out of the complete set. That is, the profile of the ideal startup could be outlined by six characteristics, but those six traits would not necessarily have to be three human features plus three founding sources, neither all the tree branches should be six-node long. A deeper tree would probably cause overfitting issues, too complex profiles on average along with too few observations.

5.2.2 Results

Let us carefully review the fruits that our decision tree has grown. Indeed, the ineludible first step is the root, and it shows very clearly that the attribute that presents the lowest level of entropy possible is to sport bank loans on the balance sheet, out of all the other financing sources, human capital features, and controls. Simply put, the probability of having chosen that attribute wrongly is minimal in comparison with all the others. The fact of having risen to the surface is not accidental.

Once the root has been examined, we can continue our path downwards, but there is no predetermined order for doing that. Therefore, we can arbitrarily move to the next stage, beginning from outer branches to inner paths. The first complete profile entails debt from banks, plus an equity infusion by business angels, and previous participation in an accelerator program too. There are women on board (but not necessarily the majority), and the firms are very old, above 33 years. The final node does not constitute a pure class, its Gini index scores 0.408, and 5 firms participated out of 7.

The second configuration reads firms with bank debt again, plus equity disbursements from angel investors too, the tenure can be considerable but below 24.3 years (the overall mean in the sample is 6.18 whereas the median is 5.0). It is not a pure class either. It registers a 0.494 entropy, which means that the attribute of the class is almost evenly distributed, a fact further confirmed by the ratio of participation, 5 firms out of 9. The third format registers loans from banks de novo, equity from business angels, but the tenure must be very high, above 24.3 years. It is the first time that a pure class is achieved, the entropy is exactly equal to 0, and 2 out of 2 firms meeting the profile participated.

When we move to the fourth contour, we now find that there is only one requirement of capital structure for meeting the profile, which is bank loans. The three has also delimited where the firm can operate featuring the health sector, along with technology and information, infrastructure and real estate, and financial services too. Finally, a tenure not higher than 7.83 would suffice. The entropy is very high, 0.499, which means that the attribute is almost evenly distributed across the node. It scores the highest number of observations in the analysis, with a participation ratio of 30 accepted firms out of 58 candidates. Simply put, this profile might or might not guarantee accelerator acceptance, but it registers the highest number of observations in the analysis. The fifth pattern is just the consequence of tightening the tenure constraint of the former. Now, the average work experience of the team should be higher than 7.83 years. The entropy is significantly lower than that of its predecessor, 0.388, registering 14 accepted firms out of 19.

Let us examine the sixth proposal. This is the first time that there is no capital structure requirement, and it could well fit some of the characteristics of the stereotype on the issue. In addition to not having endorsement by influential investors, the firm must not be old, below 4.5 years (the overall mean in our study is 2.56), and with a very low tenure, below 3.58 years. Last, the firm can operate in any sector except the real estate and infrastructure, and the financial services industries. It registers a very high entropy, again 0.49, with 4 firms accepted out of 7 applicants. The seventh profile portrays a firm with no relevant financing, not old either, below 4.5 years, but the requirement of work experience is high, more than 25.75 years. It is a pure class with no entropy whatsoever, Gini index equal to 0.0, which means that all applicants succeeded in the end, 2 out of 2.

The eight configuration is radically different in some characteristics. No relevant financing is accompanied by a very loose age requirement, the firm must be above 4.5 years, but it must not be older than 22.5. Seniority to this respect seems to be a plus. The founding experience must surprisingly be very high, more than 4.5 ventures (the mean is 1.96 and the median 1.0 in the overall population). Finally, a seniority requirement also appears when it comes to the average age of the entrepreneurs. They need to be older than 40.58 years on average. It does not constitute a pure class, the entropy is quite high, 0.469, but if counts 15 accepted firms out of 24 candidates.

Let us now analyze the ninth pattern. The start-up needs no particular capital structure element. It shows a very specific requirement for age, above 22.5 years but below 24.5. It constitutes a pure class with a 0.497 Gini score, and 13 out of 24 firms were accepted. When we transition to the tenth configuration, we find that yet again there is no capital structure requirement. The age of the applicant firm should be below 24.5 years, and that suffices for constituting a pure class with no entropy whatsoever, where 5 out of 5 candidates entered a program. Last, the eleventh profile shows the same two first characteristics of the previous one. The novelty here is that invention-based business models seem to be welcome. It is not a pure class, though, and 8 out of 13 ventures joined an accelerator in the end.

What is the contribution of this decision-tree analysis? Has our insight on the issue improved relative to our initial knowledge? To begin with, we now know about the prominence of two financing sources out of the 10 that finally achieved statistical significance in our former regressions. Five branches whose ending nodes include successful startups, whether they constitute pure classes or not, begin with debt from banks. Therefore, the relevance of that capital structure element above the other funding sources seems to be out of question. Likewise, three branches that show positive cases at the end, entail business angel equity infusions. Thus, the importance of this startup property is also confirmed. Moreover, it seems that these two financing sources can be present at the same time in the same venture, and our tree has grown three nodes (one at the fifth level, and two more at the sixth one) which show that a few firms with that double financial endorsement finally participated. The other three financing sources on the tree, debt also from angel investors, equity from friends and family, and philanthropy from governments lead to no participation finally. Apparently, no startup possessing them, along with other traits, scored a hit. In sum, Econometrics showed that the 42 initial types of financing could be reduced to 10 significant classes, and this count is further reduced now to only 2.

Second, the statistical magnitude of previous participation in another accelerator seems undeniable. It appears in one single branch but is enough for achieving positive results.

However, accelerator experience by itself could not suffice for successfully passing the screenings as it is embodied in startups with meaningful financing.

Third, the DT analysis also corroborates the role of some other variables. Work experience continues to play a tepid role as it shapes several nodes in different branches, but with mixed results. In general, tenure may help gain admission, but the requirements of that skill could vary depending on the screener and on other particularities of the business. When controlling for gender, the tree chart further confirms earlier predictions, although less intensively perhaps. And when it comes to the age of the startup, the DT exploration points to the same direction as well, even though we should admit our surprise about the high seniority of the firms involved in some nodes.

Fourth, other DT outcomes conflict altogether with the econometric results. Beginning with startup experience, this skill was always negatively considered but the CART algorithm has found some instances where not only can that ability be a plus, but intense experience could be required. Something similar happens when we examine the sectors. Technology and information and communication sectors were the only industries significant and with an important negative effect, but now some ventures could have been accepted when operating in those trades. What is more, invention-based business models, formerly reported to be clearly unwelcome, now do not seem so that much as some startups whose apparently only merits are seniority and innovation did join programs.

To sum up, financial endorsement is very important but very few financing sources can have true signaling power. Previous accelerator involvement matters too. Last, some other variables, either main explanatory factors or just controls, behave dissimilarly depending on what they are accompanied.

Below, Figures 4 and 5 portray the 11 profiles extracted from our decision tree, which has grown 26 branches in total. We have pruned the unnecessary branches and focused only on the emerged start-up configurations for improving its readability.

Figure 4. Decision tree. Profiles 1 to 6.

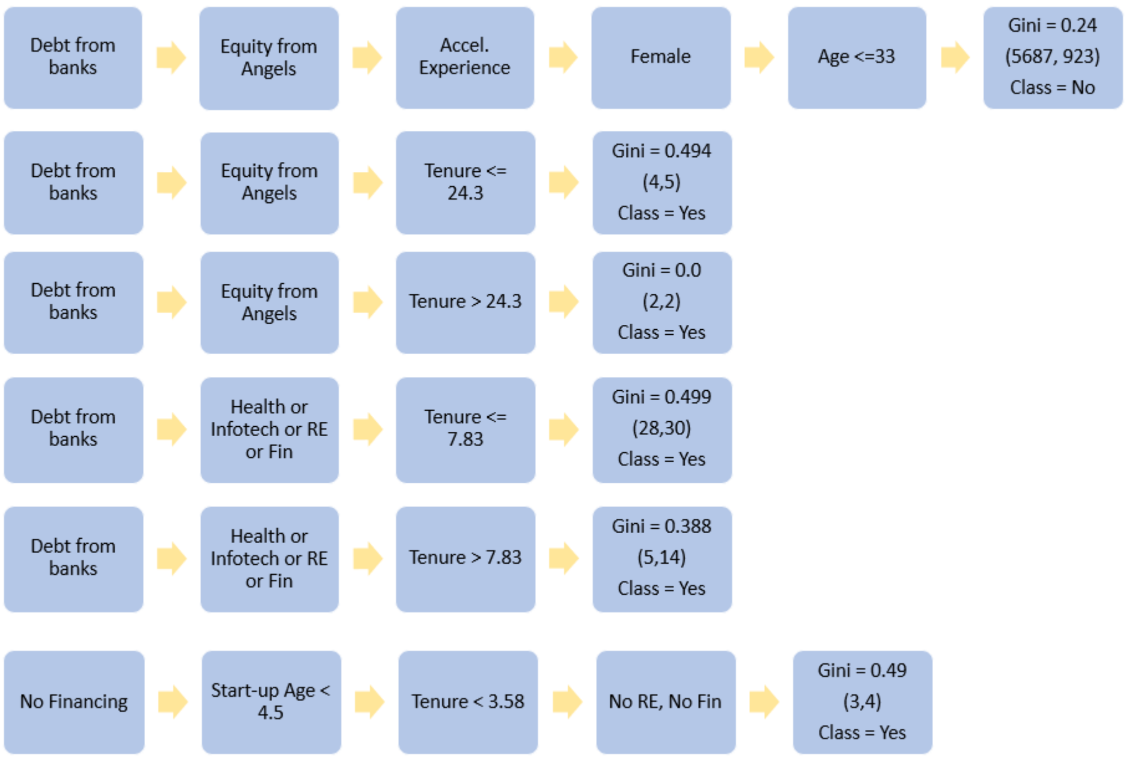
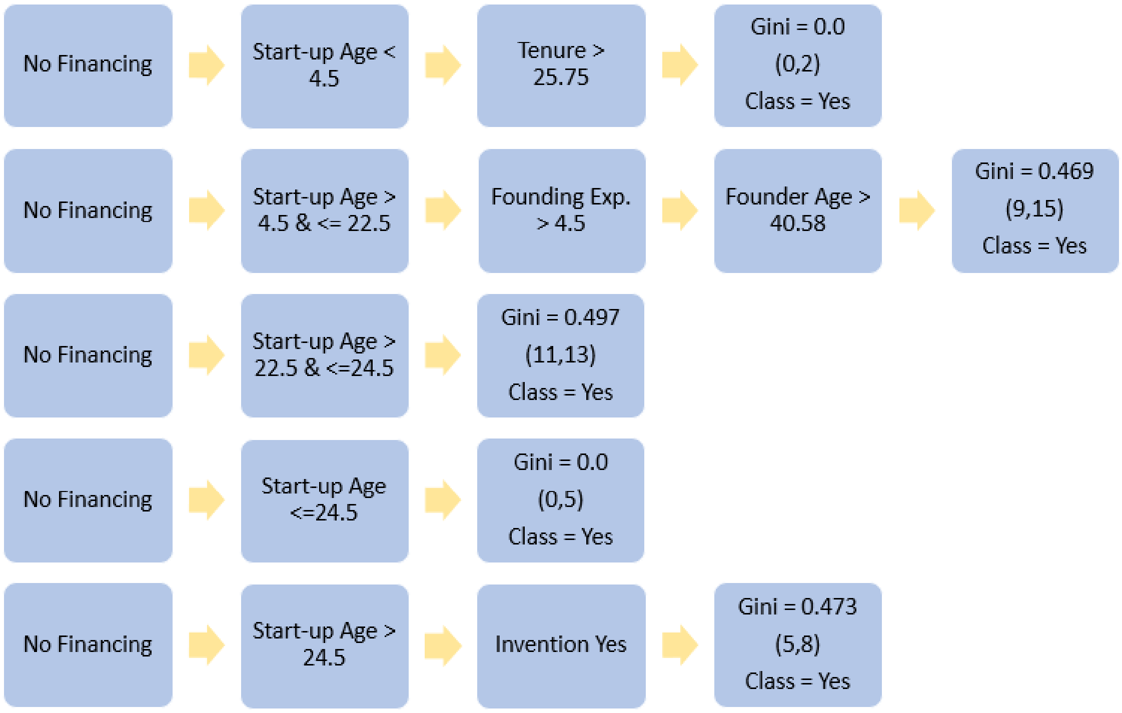


Figure 5. Decision tree. Profiles 7 to 11.



5.3 Association Rules

Despite the great insight that we have obtained through the implementation of decision trees, we strongly believe that we can acquire additional discernment for better outlining the most preferred start-up profiles. The advantage of association rules over decision trees is that associations can exist between any of the observed characteristics. Decision trees build rules with lead to one single conclusion, whereas association rules attempts to find many rules which may entail different conclusions (Hamoud, 2017). Moreover, not only are the rules generated by association rules more abundant and reliable, but also decision trees miss some of those rules. Association rules is better for large data sets and for targets with multiple characteristics (Ordonez, 2011). Accordingly, we deploy our second machine learning technique as we are convinced that our knowledge on the topic will be further improved.

Association Rules was first developed by Agrawal et al. (1993) for discovering association rules among items in large datasets in sales transactions. An association rule is a pattern that states that when an event occurs, another event occurs with a certain probability. AR soon became an interdisciplinary methodology, though, which perfectly fits our purposes as we intend to uncover relationships between two item sets, a group of startups characteristics and another set which only features one element, participation. We seek a "frequently-bought-together" association.

5.3.1 Model Specification

As with DT, AR is algorithm-driven, and out of the varied instruction sets available, we have chosen APRIORI as scholarship strongly backs it as one of the most powerful and efficient data-mining tools with an increasing use in the entrepreneurial field (Rekik et al., 2018). The internal mechanics of APRIORI is completely different than that of CART. In addition to needing no previous training, what APRIORI does, first, is to generate the total number possible of item sets that can be extracted from a database, and then create all the rules that can be inferred out of those item sets. A second major difference is that APRIORI conducts a level-wise approach. The algorithm does a first pass over all the data selecting those individual items which have been found to have a minimum support. The second pass over the same database uses only those seed items that matched the minimum support requirement. Now, the new item sets need not be individual items. The process iterates using only those sets found to be applicable in the previous screening, until no new relevant item sets are found. The name APRIORI comes, precisely, from using in every subsequent step the insight formerly gained. This is what is called the anti-monotonicity of the support measure (Agrawal and Srikant, 1994), indicator later described in this same section, which is the key property of the APRIORI algorithm. Simply put, given a frequent set of items, all its subsets must be frequent too, and if an item set is found to be infrequent, all its super sets must be infrequent too. Therefore, the hierarchical conditioning that rules the operation of DT is not present here.

There is only one drawback in contrast to the relative simplicity of APRIORI. The total number of different item sets that can be obtained from a d-item database is determined by the expression 2^d. In our work, using the complete variable set of our econometric analysis means 2^65 = 3,689*10^19 item sets, an astoundingly high number of start-up configurations. Put differently, computing work can be intensively time-consuming.

Let us now describe how the algorithm selects the rules (Azevedo and Alipio, 2007; Hikmawati et al., 2021). First, there is the support:

$$Support\ (A) = frq(A)$$

The support of an item set is just the frequency of that item set, the number of times that the item set appears in the sample, the probability of item set A occurring. It measures the popularity of A in the sample, and it is also the threshold for the algorithm to stop mining. A minimum 0.5% support requirement implies that APRIORI would stop once all item sets meeting the condition have been found out of all the item sets generated. Note that the antecedent, which is the set of characteristics that would define a winner startup profile, can be either a single feature or several different. In contrast, our consequent means just an attribute, participation.

Second, there is the confidence.

$$Confidence\ (A \rightarrow C) = \frac{Support(A \rightarrow C)}{Support(A)}$$

Be the association rule A → C, i.e., when antecedent A occurs consequent B also happens. The confidence registers how likely consequent C happens when antecedent A is present. That is, the proportion of ventures that participate in a program possessing that set of characteristics. Despite of being commonly used, one major inconvenience of the confidence is that it might misrepresent the relevance of a rule (Hussein et al., 2015). This might happen because the confidence controls for the frequency of antecedent A but not for the popularity of consequent C. Consider the case in which antecedent A has a strong support, it is very popular. Then if consequent C does also have a high frequency, occurs very often, it might be that many cases contain both just for pure chance but not because there is a real association between them instead. The next measure helps disentangle true association from sheer chance.

$$Lift\ (A \rightarrow C) = \frac{Confidence\ (A \rightarrow C)}{Support\ (C)}$$

It measures how often a rule occurs, a startup that participated in a program given a set of startup characteristics, controlled for the popularity of the consequent, how often start-ups have been accepted and participated in a program, in general. Alternatively, it can also be formulated as follows:

$$Lift\ (A \rightarrow C) = \frac{Support\ (A \rightarrow C)}{Support\ (A) * Support\ (C)}$$

The lift coefficient is probably the most efficient way to evaluate the strength of a rule. It registers the probability of consequent C happening when knowing that antecedent A is present over the probability of consequent C happening when not knowing that antecedent A is present. For instance, if the lift of a rule is 1.5, the probability of the consequent happening when we do know that the antecedent is present is higher by 50% relative to not knowing whether the antecedent is present. While the confidence is unidirectional, i.e., Confidence (A

→ C) ≠ Confidence (C → A), the lift is bidirectional. If the lift of an association is exactly equal to 1.0, it means that the antecedent and the consequent are independent from one another. There is no relationship whatsoever. When the lift is lower than 1.0, there is a negative relationship between them, they occur together less often than random. On the contrary, when the lift is higher than 1.0, there is a positive relationship, they occur together more often than random.

Prior to presenting the results of our modelling there is one important thing left, the determination of the threshold for the rule generation, the minimum support. There is no method for fixing the minimum support beforehand. On the contrary, the setting of that percentage is completely reliant on the nature of the research and on the knowledge of the researcher on the issue. What researchers using AR normally do, is to test their data with a limited number of thresholds (Rekik et al., 2018) to see whether the number of rules generated offers sufficient explanatory power for delineating satisfactorily the object of the investigation. Recently, a procedure for setting the minimum support has come to light (Hikmawati et al., 2021) but, yet again, some of the steps for that support determination are at the entire discretion of the researcher. In consequence, and after performing some tests, we have finally chosen a 1.0% support. Lower thresholds tend to explain particular cases, rather than infer general patterns, and higher thresholds generate too few rules for illustrating adequately the complexity of our subject because they render results too close to the insight already gained from Econometrics and DT.

5.3.2 Results

Our AR model has engendered 142,250 rules in total, out of which 594 meet the minimum 1% required support. This might seem too high a number at first, but poring over the results, which have been ranked by their respective lifts, extremely interesting patterns emerge. See Tables 25 and 26 below where the first 50 association rules are depicted.

Table 25. Rules 1 to 25.

Antecedents	Lift	Support	Confidence
1. Debt Banks + Age	1.711	0.010	0.294
2. Debt Banks + Higher Education + Legal Status	1.640	0.010	0.281
3. Debt Banks + Legal Status	1.617	0.012	0.277
4. Debt Banks + Higher Education	1.580	0.011	0.271
5. Debt Banks	1.556	0.013	0.267
6. Debt Banks + Target Profit	1.524	0.010	0.261
7. Equity Angels + Legal Status + Low Income	1.497	0.010	0.257
8. Financial Sector + Legal Status + Age	1.494	0.011	0.256
9. Equity Angels + Legal Status	1.481	0.020	0.254
10. Equity Angels + Higher Education + Legal Status	1.480	0.019	0.254
11. Equity Angels + Higher Education + Invention + Legal Status	1.479	0.013	0.254
12. Equity Angels + Low Income	1.477	0.011	0.253
13. Equity Angels + Legal Status + Target Profit	1.471	0.013	0.252
14. Equity Angels + Higher Education + Legal Status + Target Profit	1.468	0.013	0.252
15. Equity Angels + Invention + Legal Status	1.465	0.014	0.251
16. Equity Angels + Higher Education + Low Income	1.460	0.010	0.250
17. Equity Angels + Higher Education	1.459	0.019	0.250
18. Equity Angels	1.458	0.020	0.250
19. Equity Accelerators + Legal Status	1.455	0.010	0.250
20. Accel. Participation	1.453	0.011	0.249
21. Equity Angels + Higher Education + Invention	1.448	0.013	0.248
22. Accel. Participation + Higher Education	1.448	0.011	0.248
23. Equity Angels + Target Profit	1.445	0.013	0.248
24. Equity Angels + Higher Education + Target Profit	1.442	0.013	0.247
25. Equity Angels + Invention	1.431	0.014	0.245

Table 26. Rules 26 to 50.

Antecedents	Lift	Support	Confidence
26. Equity Accelerators	1.424	0.010	0.244
27. Financial Sector + Women + Target Profit + Legal Status	1.424	0.013	0.244
28. Financial Sector + Higher Education + Women + Target Profit + L. Status	1.414	0.011	0.243
29. Equity Angels + Higher Education + Postgraduate + Legal Status	1.411	0.011	0.242
30. Equity Angels + Postgraduate + Legal Status	1.411	0.011	0.242
31. Tenure + Women + Legal Status + Age	1.395	0.015	0.239
32. Tenure + Women + Legal Status	1.395	0.015	0.239
33. Equity Angels + Postgraduate	1.395	0.011	0.239
34. Equity Angels + Higher Education + Postgraduate	1.395	0.011	0.239
35. Tenure + Women + Target Profit + Legal Status	1.391	0.011	0.239
36. Tenure + Women + Target Profit + Legal Status + Age	1.391	0.011	0.239
37. Philan. Non-profits + Higher Education + Legal Status	1.386	0.012	0.238
38. Philan. Non-profits + Legal Status	1.382	0.013	0.237
39. Women + Upper-Middle Income + Legal Status + Age	1.382	0.011	0.237
40. Philan. Govt. + Higher Education + Postgraduate	1.374	0.010	0.236
41. Philan. Govt. + Postgraduate	1.374	0.010	0.236
42. Philan. Govt. + Higher Education + Legal Status	1.371	0.012	0.235
43. Philan. Govt. + Legal Status	1.368	0.013	0.235
44. Higher Education + Tenure + Women + Legal Status	1.365	0.013	0.234
45. Higher Education + Tenure + Women + Legal Status + Age	1.365	0.013	0.234
46. Target Profit + Low Income+ Legal Status + Age	1.357	0.011	0.233
47. Higher Education + Target Profit + Low Income + Age	1.354	0.012	0.232
48. Financial Sector + Age	1.353	0.014	0.232
49. Higher Education + Low Income + Target Profit + Legal Status + Age	1.351	0.010	0.232
50. Financial Sector + Women + Target Profit	1.348	0.015	0.231

By far, where program managers first set their eyes is on the capital structure of the candidates. We can affirm that because debt from banks along with equity infusions from business angels occupy 18 positions out of the top 20 rules. The second undeniable finding is that debt from banks is the most appreciated quality in a start-up. The top six associations are taken overwhelmingly by those startups that obtained loans from bank institutions. The lifts of those positions range from 1.524, when debt it is combined with just the intent for a profit, a target percentage at the end of the year, to 1.711, when it is startups with certain seniority who bear bank loans. Simply put, the likelihood of being accepted by a program when the first antecedent is present is 71% higher than when we do not know whether those characteristics, loans, and age above the median, are present in the startup's complete set of characteristics. Only bank loans plus seniority suffice above any other combination. 1.711 shows a considerable dependence between the antecedent and the consequent, participation. Interestingly, debt from banks never appears again across the 588 rules left. Neither on a stand-alone basis, nor combined with any other feature.

The second capital structure element is equity infusions by angel investors. It appears 20 times along the first 50 associations, and their lifts range from 1.395 to 1.497, when combined with education and with the region where the start operates plus a for-profit legal structure, respectively. Clearly, the lifts of equity from business angels are always consistently lower than those of debt from banks but they still display a remarkable strength between antecedent and consequence. When we focus on the pure attributes for assessing their true effects regardless of any other backing feature, debt by itself generates a 1.556 lift whereas equity from angels as a stand-alone antecedent, registers 1.458. Similarly to what happens to debt, angel equity never appears again on the list once we move from the 34th rank downwards.

The next financing source that is registered is equity from accelerators themselves. As formerly pointed out in this work, we cannot ascertain whether that means just the usually meagre quantity that programs invest in their portfolio companies, or if, on the contrary, it is subsequent follow-on investment on promising ventures after completing their training. We incline towards the second option, as earlier participation is very positively regarded too. The lift of this antecedent, when combined with for-profit incorporation, is quite high, 1.455, ranking above 8 angel equity positions. Further, when it materializes on isolation, rank 26, the strength of the rule is also considerable, 1.424, even before 4 combinations featuring business angel financing. Identically to bank debt and angel capital infusions, it never shows up again.

The fourth and fifth financing sources are both philanthropic supports. The first is philanthropy by not-for-profit organizations. It ranks accompanied by education and for-profit incorporation, and by for-profit incorporation only in the 37 and 38 positions, respectively, and their lifts are 1.386 and 1.382, strong enough to depict sound rules. The second type of philanthropy is from governments. It ranks slightly below, but it appears four times consecutively, from place 40 to place 43, 1.374 to 1.368 lifts, respectively. Interestingly, these two types of financing are the only ones that appear again once the 50th position has been passed downwards, but while philanthropy from non-profits does so lots of times, when it comes from governments it happens again only one more occasion (rank 157, lift 1.237). When the former means the whole antecedent by itself, it ranks on the 254th place, with a very low 1.185 lift, whereas governmental giving never constitutes a complete antecedent on its own. No other financing source does appear throughout the whole rule list, neither alone, nor combined, out of the 17 types of equity, the 15 classes of debt, and the 10 sorts of philanthropy featured in our database. Therefore, the role of the capital structure elements is explained.

Time to move on to human capital features, now. Higher education matters and matters a lot. When we mean higher education in general, from possessing a Bachelors' degree to a PhD included, the skill appears 18 times out of the first 50 associations, including the second general position of the complete list coupling with debt from banks, with 1.640 to 1.351 lifts, which clearly indicates that a good education endowment is welcome but so long as it is accompanied by other start-up characteristics. Virtually any other venture feature can be found among its antecedent companions across the rule catalogue. However, higher education in general on a stand-alone basis only shows up in a rather disappointing 572 position showing almost no relationship with the consequent, a 1.015 lift. Postgraduates are positively considered too but with a lower strength. The first time they rank in the 29th emplacement with a good 1.411 lift, and they repeat 5 more times within the top 50 (the lowest scores 1.374). As with happens to higher education in general, it combines well dozens of times across the list but when it shapes a single-feature antecedent, position 505, its lift reveals the weakness of the association, 1.054, only slightly above than simply graduates. When it comes to PhDs, they never appear until positions 585 to 588, four in a row, depicting also the four combinations possible with the higher education and postgraduate variables. This explains clearly that higher education *per se*, irrespective of its level, is not enough for convincing accelerator managers that the venture will come to fruition in the end. Conversely, simply bank or angel endorsement do. The other two education variables left, schooling years and the education ratio only appeared in models with lower supports.

Managerial experience when proxied by tenure is well received too, although it first emerges in the 32nd position, for repeating five more times within the short list. Their lifts range from 1.395 to 1.365, which show good rules provided association with other elements is assured. They seem to mix particularly well with women as they are present in all those six instances. It repeats lots of times but on isolation only ranks in the 282 position, with a very low 1.166 lift.

The stance of program screeners with respect to founding experience is also worth mentioning. Prior startup experience in general, regardless of the type of organization, whether for-profit or of any other class, appears for the first time in the 80th place with a 1.299 lift. That is, having founded at least one firm in the past is considered positively, but once again, as long as the antecedent also features other startup characteristics. Moreover, the skill is also found in multiple antecedents, but they normally contain two to three features more at least. This is another clear example of how one attribute can be regarded depending on its circumstances. Program analysts seem to carefully ponder the pros and cons of recruiting teams with such experience, and a wide backcloth for better valuing the skill is a *sine qua non* condition as it never appears on isolation out of all the rules.

Let us focus now on the physical characteristics of the entrepreneurs. The average age of the founders plays no role in the AR tests. This fact suggests that programs simply do not care about that, that they pay attention to whatever other element. As for women in teams, they do not arise until the 27th place, 1.423 lift, for repeating 9 more times in the tables, and lots of occasions more in the whole analysis. When they are the majority, rank 55, lift 1.341, the antecedent must also include only a target profit and being registered as a for-profit organization for reaching the consequent. This is limpid evidence that the presence of women may help gain accelerator acceptance in many situations.

Skimming very fast the AR tables, one could say that that is an oddity, but it is not. The financial services sector ranks very high, and for beating almost all combinations of angel endorsement the only thing its needs it to be embodied in a startup older than a year which has been established with lucrative intent. No other emblem is necessitated. It registers a 1.494 lift, and it shows up 4 more times in the tables, totaling 34 occasions in the complete rule menu, even appearing once in isolation. Thus, the relevance of such sector is amply signified.

As commented above, in this AR context, the start-up age variable registers whether the firm is at least one year old. It appears lots of times combined with many other characteristics, and at the same time there are also many associations which do not feature this variable in the antecedent. Therefore, this is consistent with the common wisdom about the approbatory attitude of programs with respect to ventures at their earliest stages.

Let us examine now how innovative business models are seen. Innovation helps shape 4 antecedents among the top 50 rules, and the top rank reached is the 11th, 1.479 lift. Not surprisingly, all those instances also register the presence of business angels in the capital structure of the firm. Innovation shows up again many times across all the antecedents in the sample and out of all those examples postgraduates also appear 43 times in the item set. Curiously, PhDs never appear associated with innovation or angel investors. Therefore, the perceived risk of invention-based models may be mitigated significantly when business angels back the involved start-ups.

Accelerators also welcome the presence in the start-ups of other accelerators, either through equity infusions, as earlier mentioned, or just because of having participated previously in another program. Accelerator experience markedly ranks in the 20th position on a stand-alone basis, with a 1.453 lift, and then in the 22nd place, along with higher education with a slightly lower lift. Thus, even when the antecedent is only formed by the sole quality, it may open the way to participation. Interestingly, and despite its strong effect, the attribute is never registered again. Last, the legal status of the firm has an enormous presence throughout the sample, across many different combinations with other qualities. Conversely, whether the firm has social or environmental motives shapes no antecedent, neither in whole nor in part.

6. Reconciliation of the Results

6.1 Reconciliation of the Results

The fulfillment of the two phases of the third objective of our work has led us to obtain three sets of results. One statistical set, which features our full econometric model, and two machine learning bodies, decision trees and association rules' output, respectively. However, prior to reviewing such outcomes we should insist on a fundamental aspect. Econometrics and Machine Learning produce cannot be directly compared because they indicate different things. While statistics denotes whether the variables are relevant and their supposed effects by themselves, machine learning signifies combinations of attributes. Therefore, we do not mean here further hypothesis validation, but the assessment of what start-up attributes contribute the most to creating a winner profile.

First, we have grouped the variables according with the two main dimension blocks of our research, namely, human capital variables and capital structure elements, plus a third section featuring the controls. The variables are ranked, within each block, according with their relative importance with respect to each of the three approaches.

When in Econometrics, they are categorized according to their respective odds ratios. When in DT, they follow the same order that when they wind their way down along the tree branches. Last, when in AR, the variables are graded with respect to the lifts of the antecedents in which they are featured, and to whether the focal variable is the only one that conforms that antecedent or not. Shaded in green are reported those variables that have registered a positive effect, i.e., increasing the likelihood of being accepted in a program when in Econometrics, or leading to a successful profile when in DT, or being a part of a winner contour in AR, whereas those factors shaded in yellow mean variables that presumably decrease the acceptance probability. The blue shading signals variables that appeared in profile proposals but did not end in accepted firms in the end.

Beginning with the funding sources, we see that the ten-item list of Econometrics is reduced to five sources in the DT analysis, and the source count holds when using AR. All the financing sources in Econometrics register a positive effect except equity from friends and family and capital infusions from governments. In turn, DT portrays the three types of financing, namely, equity, debt and philanthropy, but only debt and equity lead to accepted firms in the end. When we move to AR, the three sorts of funds are featured in winner antecedents in the short list. However, only bank credit and equity capital from business angels lead to positive outcomes in the three columns.

Relying on AR, we can say that out of the ten statistically significant sources from Econometrics, only five are able to attract the attention of accelerator managers, and out of those five, only three of them can reasonable be attributed enough signalling power for doing so on a stand-alone basis. The other five sources have no effect in our sample, they do not shape any antecedent in the complete rule list. Therefore, who finances you matters, and it matters the most if that financier is either a bank or a business angel without excluding accelerators themselves as equity investors.

When we move on to human capital variables, results are dissimilar too. Higher education in general is not significant when scrutinized with both probit and logit and DT classification. However, it is very meaningful in AR. Lots of rules display higher education in general at the top part of the association list. Higher education combines very well with bank loans, and it seems that angel investors value positively well-educated teams. The unenthusiastic support that postgraduates receive in Econometrics attains additional reinforcement in AR as we can see them in some combinations with both equity from angels and from philanthropy too but, curiously, no debt antecedent features masters' degrees. In contrast, they do not appear in DT. In fact, education is absent in DT. Similarly, we could say that PhDs are unseen in the three scenarios. They are not significant in regressions, and when present in AR they are so in the last rules and, most interestingly, only combined with other education variables, never with any other attribute. We can conclude that higher education, postgraduates included, is very relevant and has ostensible signalling power as evidenced by the many combinations in the top AR rules. The point is that for higher education to effectively radiate its signal, it needs to be accompanied by other attributes, it dilutes otherwise. When they shape an entire antecedent on their own, they rank at the very bottom of the AR list.

Work experience, regardless of its seniority, turns positive results everywhere. It ranks disparately across the three methods but is always positive. Perhaps, DT is the technique that gives it a greater value, followed by AR. It signals positively the team, but, once again, its effects are better perceived when mixed with other properties. Tenure by itself has little or almost no power. In contrast, start-up experience registers contradictory outcomes. When using regressions, its effect is almost negligible but negative in any case, whereas when in DT and AR its sign changes to positive. It is clearly always found clustering together with other qualities, though. Nevertheless, its influence is very low across the three methods. Thus, the initial effect from Econometrics is openly questioned when, once again, we see the skill in combination.

Finally, it is worth noting that despite this work pivots around the presumed importance, contrasted in many cases already, of a set of human and financial variables, other parameters not key at first, the controls, have tuned out to be relevant on many occasions in light not only of the econometric results but also of the big data outcomes. We do not just mean that the effect of some of those controls change when we move from statistics to machine learning, such as the case of invention-based business models, or when other otherwise unnoticed factors have risen to the surface, such as the financial services sector. Rather, we accentuate that some of them, whether isolated or in multiple-item antecedents, conform winning start-up profiles. Some relevant examples can be rule number 8 in AR, with an antecedent composed by the financial services sector, the legal status, and the age of the firm. Three supposedly less important control variables intended to qualify the main explanatory factors suffice for ranking at almost the top of the AR classification, and other examples can be found in that short list too. However, the most outstanding instance is previous participation in another program. It attains the highest grades possible across the three types of research conducted here including the top rank in regressions above any other feature. All those instances, to name but a few, could prompt some questioning about their role in future research. Table 27 portrays the categorized variables and their effects.

Table 27. Reconciliation of the results

Econometrics	**Decision Trees**	**Association Rules**
Human Capital Variables		
1. Postgraduate	1. Tenure	1. Higher Education
2. Work Experience	2. Founding Experience	2. Postgraduate
3. Founding Experience		3. Work Experience
Capital Structure Variables		
1. Debt Angels	1. Debt from Banks	1. Debt Banks
2. Equity Angels	2. Equity Angels	2. Equity Angels
3. Debt Accelerators	3. Debt Angels	3. Equity Accelerators
4. Debt Banks	4. Equity F&F	4. Philanthropy Non-profits
5. Philanthropy Non-profits	5. Philan. Governments	5. Philan. Governments
6. Equity Venture Capital		
7. Equity Accelerators		
8. Philanthropy Governments		
9. Equity Family & Friends		
10. Equity Governments		
Controls		
1. Accelerator Experience	1. Accelerator Experience	1. Accelerator Experience
2. Legal Status	2. Invention-Based	2. Start-up Age
3. Upper-Mid. Income Region	3. Start-up Age	3. Legal Status
4. High Income Region	4. Female	5. Target Profit
5. Low Income Region	5. Infotech. Sector	6. Financial Sector
6. Female		7. Low Income Region
7. Target Profit		8. Invention-Based
8. Start-up Age		9. Female
9. Invention-Based		10. Upper-Middle Income
10. Infotech. Sector		

We believe that Machine Learning and, above all, Association Rules is the most appropriate approach for conducting this type of research because this is the only methodology that can find concrete combinations of variables that help outline distinguishable start-up profiles. We did not intend to assess only whether one particular factor, or a series of them, might influence the decision of program managers when selecting their next investees. A start-up is not the mere addition of a group of qualities. If a venture were so, then, comparing its isolated attributes against the appropriate benchmark would suffice for forecasting future success or failure. Rather, it is the combination of those properties what shapes a final single unit and we wanted to ascertain what combinations are more valued. We needed a holistic approach, and this is the approach that we have used. That said, we also want to emphasize the indispensable usefulness of traditional Econometrics. If Machine Learning can give us what statistics cannot, the opposite is also true. Econometrics supplies us with invaluable information about the variables under scrutiny, that is, properties of the estimates, such as regularities, confidence intervals, intensity, and, ultimately, their statistically significance. Therefore, both fields should be used.

6.2 Is there an Ideal Start-up Profile?

Out of all the combinations possible, two different start-up profiles stand out clearly, and the only two things that they have in common is the dominance of their respective capital structures on the one hand, and that they score the highest participation rates, respectively, on the other. As for everything else, they are completely different. Table 28 below summarizes the descriptive statistics of the two winner profiles. Let us carefully examine each parameter, one at a time. First, the presence of ventures that raised equity infusions from business angels is much higher, roughly by 60% (1,254 firms versus 786). However, the percentage of firms that finally participated is higher for those firms backed by banks.

Concretely by 8.92% (26.84% versus 24.64%). Interestingly, only 75 start-ups have got both debt from banks and equity from business angels, 0.46% of the total sample. 4.79% Took out only debt, and 7.63% raised only equity. Therefore, the top rank described in AR for bank debt-shaped antecedents is further corroborated here. The first line of Table 28 registers the number of ventures that featured each type of financing out of the total number of observations, 16,426. The second line reads the respective percentages of program participation according with that type of funding, and the percentage of accelerator acceptance with respect to the total sample, 17.04%. The double-entry lines below portray the mean of each magnitude on the first column and its standard deviation in parentheses.

Table 28. Comparison between firms with bank loans and firms with equity from angels

	Debt Banks	**Equity Angels**	**Overall Sample**
Capital Structure	786 -	1,254 -	16,426 -
Participated	26.84% -	24.64% -	17.04% -
Schooling Years	31.574 (11.830)	35.900 (11.582)	31.331 (12.145)
Postgraduate	0.441 (0.497)	0.567 (0.496)	0.415 (0.493)
Founding Exp.	2.252 (2.902)	2.846 (2.966)	1.964 (2.583)
Work Experience	8.053 (5.523)	6.488 (4.548)	6.176 (5.020)
Start-up Age	6.047 (6.693)	2.555 (2.465)	2.559 (3.826)
Age Founder	39.404 (9.800)	35.431 (8.469)	34.834 (9.135)
Female	0.716 (0.688)	0.415 (0.638)	0.635 (0.730)
Invention-Based	0.496 (0.500)	0.707 (0.455)	0.532 (0.499)
Accel. Participation	0.052 (0.222)	0.080 (0.271)	0.050 (0.217)

Second, both patterns unarguably beat the average participation rate, which is 17.04%. Leveraged firms do so by 57.5% (26.84% versus 17.04%) whereas angel-backed start-ups do it by 44.60% (24.64 against 17.04). Their similarities end here.

Entrepreneurs who reach agreements with angel investors are much more educated individuals, either when we consider their overall education endowment through the total years of schooling, or when we esteem the presence of masters' degrees in the teams. When the difference is measured by the former, the gap is very wide, indeed, 4.326 on average. The distance when it comes to the presence of postgraduates is not that long, though. It is not that the entrepreneurs who succeed negotiating with lending institutions are not well educated, their averages match almost perfectly the means of the overall sample. It is simply that founders who seek and obtain angel financing are much better trained. Again, the education factor is properly registered in AR, which, besides shows no postgraduate-and-debt combination whatever.

Although teams using debt have formerly founded 2.252 ventures on average, which is a higher number than the general mean, 1.964, again, angel-backed entrepreneurs now show greater founding experience. Specifically, by 26,28% (2.846 firms versus 2.252). Thus, angels would care more about seasoned individuals to this respect, entrepreneurs who have already faced the toughness of the market. Since we cannot know the sign of that former experience, positive or negative, it could be that previous failure would not have negatively signalled some teams. The lower figure when bankers are in the business could mean that those financiers simply focus more on the ability of the start-up for servicing the debt.

When we examine the work experience, it is now levered ventures who take the lead. Their average is 8.053 years whereas that of angel-backed is 6.488, a 24.12% higher. Then, banks seem to care more about business experience regardless of the seniority. Their main concern could be whether their borrowers can lead their ventures to scenarios where the internal routines of the businesses are well established already, which could imply better organization and administration of the proceeds for better servicing the loans. On the contrary, angels would care more about the ability to beat the market as mentioned in the former paragraph.

It is when the age of venture is addressed when we find the greatest difference between the two types of ventures, and it is just awesome. Firms using debt from banks are 2.37 times older than their counterparts, 6.047 years versus 2.555. Angel-backed firms are in line with all the other ventures in the sample to this respect. It is leveraged firms who are much older. It is also worth noting the standard deviation to further understand the distribution of such magnitude across the three columns. Ventures with bank debt have also the greatest standard deviation, very high indeed, which means that we can find even much older firms within the subsample (or firms converging to the overall mean too). This could confirm again the desire of bankers for more stable organizations. Therefore, the highest antecedent in AR, which only features debt from banks plus the seniority of the firm, would not be by chance. In contrast, the standard deviation with angels on board is lower than even that of the overall sample. Put differently, start-ups which obtained financing from business angels are concentrated in a very narrow swath, which suggests that angels target very precisely the stage of their deals.

The age of the entrepreneurs is also one of the hallmarks that neatly divide our two-profile universe. Founders in indebted firms average 39.404 years while the other group turns a 35.431-year mean. Both figures are higher than the overall score, but borrowers are definitely much older. Again, the standard deviation of the angel column is the lowest. Thus, angel investors also care about the age of their teams, they may prefer younger founders. And vice versa, moneylenders would care more about seniority to this respect. In sum, the factor count that would point to risk-proneness above stability is listing gradually to angel-backed ventures.

Surprisingly, business angels seem to dislike women as members of the ventures where they invest. It is not only that the average of bank-backed firms is higher than that of the overall sample. It is that angels allocate less money in ventures with higher presence of women. The difference is suggestive, 72.53% less. The same happens when we examine whether women are the majority in the teams (not registered in Table 13). Indebted firms led by women score 0.206, whereas its counterpart counts 0.110. However, despite the statistics is clear, no women appear in the AR rules involving debt, which may suggest that for accelerators accepting those start-ups the requirement of women in the teams is not a sine qua non condition.

As Table 28 depicts, business angels clearly bet on innovation. The average of their investees is 0.707, whereas the overall mean is 0.532. As it could be reasonably expected too, start-ups with debt on their balance sheets are appreciably less innovative. Bankers could be reluctant to increase their risk exposure through investing their monies in business models not fully proven yet.

Now is the turn of previous participation in other accelerator programs. We see that angel backed firms register a considerably higher rate than leveraged firms. While the former reads 0.080, the latter displays 0.052., which is almost exactly equal to that of the complete sample. Therefore, this would be evidence contrary to common wisdom because it seems an inversion of the financing sequence stereotype already described by the literature (Pierrakis and Owen, 2020).

In our analyses the founder count is not relevant. It is not statistically significant in Econometrics, and it is not relevant in DT and in AR either. However, we believed worth exploring the variable to see whether some more insight could be gained. And yes, there are substantial dissimilarities, which are registered below in Table 29. Business angels have an obvious preference for complete teams, rather than for couples or soloists. 44% Of their allocations were invested in three-person groups, while the total average is 33.7% and the mean of firms which took out debt is even lower, 33.3%. In the same vein, the very low allocation rate registered when they invest in lone entrepreneurs enhances this fact. The general mean for soloists is 26.5%, followed by indebted firms with 24,0%, and far from them, angel-funded start-ups with only one person at the helm, 15.7%.

Table 29. Team size and financial endorsement: bank debt versus angel equity.

	Debt Banks		Equity Angels		Overall Sample	
Capital Structure	786		1,254		16,426	
Solo Entrepreneurs	189	24.0%	197	15.7%	4,359	26.5%
2-Person Teams	335	42.6%	505	40.3%	6,539	39.8%
3-Person Teams	262	33.3%	552	44.0%	5,528	33.7%

We now examine the distribution of the two profiles across income regions for exploring whether the access to those sources of funds is evenly distributed. Results are depicted in Table 30 below. The region with the lowest income per capita reports that sourcing capital from business angels is really difficult. It scores just a 1,4% of the angel allocations, while the respective percentages for bank credit and the whole sample are 6.9% and 6,1%. That circumstance is little more than an exceptionality. As we climb to higher income areas, the presence of angel equity increases noticeably, until the top income zone, which shows a 53.7%. In contrast, the presence of debt is higher in the middle areas than in the highest zone. This could be explained by the economic development of each region. For there to be an abundance of business angels, it is indispensable an area where economic growth can be high and steady. Business angels do not usually invest in companies that are located very far from where they do their daily life (Shane, 2005).

Last, we pore over the industries where the two profiles operate preferably. Banks clearly support consumer-based ventures, with a 36.7%, followed by the energy, raw materials, utilities, and industrial sectors with a 15.1%. This could be consistent with business models expected to have a recurrent generation of cashflow for securing the service of the debt. On the other hand, we find angel-funded firms more evenly distributed across that industry classification, but with two exceptions, the financial services industry, and the consumer sector, with 21.39% and 29.3%. Interestingly, all the top AR rules that feature the financial services sector do not include business angels in their respective antecedents, which may suggest that the start-ups which operate in that industry need not additional signalling power, neither from angels nor from banks.

Table 30. Distribution of bank debt and angel equity across income regions and industry sectors

	Debt Banks	**Equity Angels**	**Overall Sample**
Low Income	0.069	0.014	0.061
Lower-Middle	0.324	0.211	0.295
Upper-Middle	0.325	0.238	0.259
High Income	0.282	0.537	0.385
Obs.			16,362
	Debt Banks	**Equity Angels**	**Overall Sample**
Energy/Materials/Utilities/Industrial	0.151	0.101	0.134
Consumer	0.367	0.293	0.355
Health	0.110	0.132	0.107
Techno & Info & Comm.	0.073	0.100	0.099
Real Estate	0.042	0.017	0.025
Financial Services	0.055	0.219	0.082
Others	0.201	0.138	0.198
Obs.			16,319

6.3 Summary of the Findings

First, accelerator acceptance is clearly driven by capital structure elements above the human capital endowment. Three types of outside financing, namely, debt, equity, and philanthropy are present in the top associations, which suggests that accelerator managers first set their eyes on the prospects of the business rather than in the talent of the start-up promoters. Second, debt from banks is, by far, the most appreciated quality by programs above any other possible combination, either debt on a stand-alone basis or associated with other properties, and it might grant accelerator acceptance by itself. Third, the endorsement of business angels is also very important. It might also pass accelerator screening successfully on its own, and it can even be found in more associations than bank credit. This could be more aligned with common wisdom on the field, the supposedly J-shaped curve in the venture capital financing pipeline, although with a reversed order, first business angels, second accelerators. Fourth, interestingly, both types of financing rarely appear together in the same venture, which reinforces the insight into the existence of two different venture profiles. Fifth, higher education has a strong signalling power but only when it appears along with other start-up attributes. It is the human capital variable most present in the AR analysis. Sixth, tenure, i.e., work experience in general regardless of seniority, is also relevant but, as in the case of higher education, so long as it is combined with other firm characteristics, never on its own. It appears in many associations. Seventh and last, there are two markedly different risk profiles. Start-ups with angel financing presumably have riskier business models, which can be denoted by the higher innovation-based-ideas coefficient, a higher presence of postgraduates who are also younger than its counterparts, and a higher rate of previous accelerator participation, which could match to some extent the stereotype of innovation-driven businesses and the intent to scale up as soon as possible. In contrast, credit-funded firms have older entrepreneurs, less educated, with less postgraduates on board, but with much higher work experience in general, which would point to more stable, slow-growing firms managed by people who could me more used to well-established routines intended to meet the burden of debt service on a timely basis.

6.4 Why are these Findings Important?

Our findings are important because, to the best of our knowledge, this is the first time we have got insight into the way accelerators comprehensively evaluate their prospective portfolio companies. Other woks have approached the topic but, in addition to sample dissimilarities, all of them lack the holistic approach. Those studies provide valuable information but all of them fail at depicting a thorough profile, since they can only portray how different variables behave per se, but not when combined, something which goes beyond presumed synergistic effects. The literature reflects (Pierrakis and Owen, 2020) that there is an important proportion of publicly-funded and hybrid accelerators. A better and overarching knowledge of this phenomenon, which places itself at the very beginning of the venture capital pipeline, could only help a better allocation of the economy resources.

7. Robustness

Our research problem is whether there is an ideal start-up profile or, if on the contrary, there is no such thing. However, prior to addressing this research goal through a comprehensive view, we also wanted to ascertain the current research's state of the art on the field. We also wanted to shed additional light on the separate relevance of several different start-up characteristics as we found the extant literature to be rather inconclusive on the role of many of those commonly accepted drivers of successful early-stage financing in general, and of accelerator acceptance in particular. Therefore, for fulfilling such pretension, which is featured in objective 2 and the first phase of objective 3 in this work, the use of Econometrics suffices. It is the ideal method for verifying the statistical relevance of an item, i.e., whether the attribute is pertinent to the focal problem or not, and the impact of its presence.

That said, we have first dealt with the issue of how better capture those dimensions strongly backed by the extant literature as they are not uniformly defined. Our reply to this first problem has been the multiple variable recoding, i.e., to encapsulate every focal dimension, either human capital attributes or financing sources, into several different variables not to miss any nuance of the property under scrutiny. For instance, the educational background of the candidates has been proxied by 5 distinct variables, each of which captures a different facet of the same dimension, ensuring a thorough coverage. Multiple recoding of the raw data supplied by the original database is a strong robustness test by itself, in the sense that it can either corroborate or refute the research questions raised around it and the ensuing hypotheses. Simply put, all our econometric tests have shown no contradictions. All the tested variable sets have always ranged from no significance to negative impact on the one side, to no significance to positive impact on the other. Therefore, we consider our results relative to the separate role of each dimension robust.

Second, we have treated the overall sample downsizing it to include just three-person teams as the database only features detailed information on those start-ups. Otherwise, results would have been completely biased as there are 6,939 teams with more than three entrepreneurs on board out of 16,426 start-ups.

Third, the selection and the final inclusion of the explanatory variables in the econometric models, both the partial model featuring only human capital dimensions and the full model involving also financing sources, have been done according to two criteria. First, considering only those factors widely recognized by the literature. Second, signifying those attributes through only statistical procedures, not by a trial-and-error process, or randomly. A thorough descriptive statistics of our complete sample has been performed, and then we have conducted the already mentioned T-tests of equal variances, and the Mann-Whitney-Wilcoxon rank sum tests for verifying whether the exogenous factors might contribute true explanatory power, i.e., if they register different values according to participation in a program. Therefore, the final choice of the variables responds solely to their underlying relevance.

Fourth. We follow Hahn and Soyer (2005) when we choose probit as our main model. However, we have also used logit regressions for a twofold purpose. On the one hand, for supplying with odds ratios since they are more easily interpretable than marginal effects. On the other, as a robustness test too for double-checking the statistical significance and the effect of the variables involved in our probit outcomes. The results of both sets of regressions, probit and logit, are virtually identical.

Fifth. In such a large dataset outliers could not be absent. We have addressed the issue through a double approach. First, we have treated our sample by trimming those observations beyond percentile 99 when appropriate. Besides, following Wooldridge (2013) we have also used robust standard errors in our regressions for variable validation purposes to enhance the statistical significance of our results. Robust standard errors mitigate the effect of outliers so that the quality of the estimates is reinforced.

Sixth. We have implemented double sampling. This is the strongest robustness test that can be performed when conducting research over a database such as the GALI 2020. The Emory University offers researchers a wondrous data set, which builds on self-fulfilled questionnaires sent to the start-ups. Unfortunately, and despite the high quality of the data, the base contains many missing observations, which could significantly distort the regressions' output. We have addressed the issue through constructing a second database, which is based on the original one, performing imputation over the censored data using Tobit regressions (Allison, 2000; Beck et al., 2011; Cotei and Farhat, 2017). The missing values are then replaced by the Tobit predictions. This is appropriate when knowing the range within which that censored data is supposed to be. Since the variables being imputed are bounded by zero on the left side, the regressions are truncated. Subsequently, for addressing outlier issues that could distort our Tobit predictions, we have set limits equal to percentile 99 on the right side of all the imputed elements.

The Tobit model expresses the value of the dependent variable, *y*, in terms of an underlying component, *y**. *y* is equal to *y**, when $y^* \geq 0$, but $y = 0$ when $y^* < 0$.

$$y = \alpha + \beta^* X + U; \;\; U/X \sim (0, \sigma^2)$$

$$y = \max(0, y^*)$$

Tobit requires that the latent variable *y** is normally distributed. Thus, *y* would follow the normal distribution too but over only positive values. As when implementing T-tests of equal variances earlier in this work, we do know that this is not the case but, again, that circumstance is overcome thanks to the Central Limit Theorem (Wooldridge, 2013).

Once imputation has been carried out, we have conducted again all the regressions performed over the non-imputed database. The results are virtually identical, no variable changes its statistical significance and its effect either, with one single exception which is equity infusions from governments. In the non-imputed regressions, as the data is freely supplied to all researchers, the variable registers a very negative effect. However, when regressing the imputed data, the variable becomes not significant. It is worth noting that that variable never appears in Machine Learning outcomes. Therefore, we consider our Econometrics results definitely robust.

It is at this point when we have transitioned to a holistic approach for addressing our research question, since a start-up constitutes a completely different reality than the sum of its constituent parts. And again, for dealing with this comprehensive perspective, we have followed a double approach. We have used two different machine learning techniques, decision trees and association rules, which has enabled us to capture every possible underlying start-up profile out the complete universe of venture attributes available. The results of decision trees and association rules are robust too because they complement each other as it could be reasonably expected since, as formerly pointed out in this work, association rules is likely to include all the configurations shaped by decision trees and also capture all the others that could have been missed.

Last, even though econometric results and machine learning outcomes are not directly comparable, they mutually reinforce. While Econometrics highlights what attribute is statistically significant and its impact per se, it is machine learning that tells us when or how that characteristic attains its relevance. Hence, we have seen that our econometric results hold when we transition from a methodology to another, which also constitutes a remarkable robustness test. Honestly, we believe that this is the stoutest cross-validation we could think about.

8. Discussion

8.1 Discussion and Conclusions

We started this investigation for solving our research problem, i.e., what the ideal start-up profile is when it comes to accelerator acceptance, and we thought it appropriate to conduct our exploration through a phased approach, the first part of which dealt with the relative importance of the different founder skills when facing program screening, our research question 1, whereas the second part addressed the comparison between the human capital endowment of an applicant firm and its financing structure, research question 2, what accelerator managers prefer, the former or the latter.

Given the results of all our analyses, we strongly believe that program managers bet first on the business as proxied by its financing sources rather than on the team, although this preference does not preclude them from considering human capital dimensions heavily too. We base our conclusions on the overwhelming evidence accrued by our research, relying above of all on the Machine Learning results, already anticipated to a relevant extent by Econometrics. Our preference for the big data outcomes above any other methodology is rapidly told, since machine learning are the most appropriate techniques for unveiling what would have remained hidden otherwise, i.e., venture profiles. This is the only possible way to solve our research problem, the reaction of accelerators in front of an entity, the candidate firm, which is not the mere addition of a series of qualities. Those attributes considered together shape something distinct. The whole is not the sum of the parts.

When accelerators first select start-ups which display bank credit on their balance sheet, they clearly bet on a proven ability of that applying venture for self-sustainability. Otherwise, that firm would not have obtained a loan from an institutional investor even if that credit had been collateralized with the entrepreneurs' personal assets. The business of banks does not consist of seizing collateral from non-performing loans. Accelerators seem to embrace willingly the bank screening, which could appreciably mitigate the adverse selection involved when sourcing portfolio firms. Additionally, as earlier discussed in this work, indebted firms could also show a lower ownership dilution, which could facilitate accelerators easier and more profitable exits when their investees try to secure follow-on equity financing at the end of the program. Cashflow-yielding ventures whose owners still retain most of the ownership could translate into higher returns for accelerators around the demo day, which could enhance their survival prospects, especially of those privately-sponsored.

Likewise, when programs select firms with angel investor endorsement, they bet again on a financial structure element. It could be argued that when accelerators do so, they indirectly bet on the team because this is what angels do. However, we posit that this view corresponds only to a stereotyped image of how business angels confront their investment opportunities. Business angels take very seriously their allocations (Kerr at al., 2014) and their intentions go far beyond simply experiencing feelings of empathy. Moreover, scholarship has evidenced that angel investors behave quite differently when they act as lone investors in comparison with when they team other peers to form groups (Wiltbank and Boer, 2007; Shane, 2009). Business angels in groups deploy screening procedures much like venture capitalists do, and it is unquestionable that venture capitalists bet on the horse as it has been fairly demonstrated (Gorman and Sahlman, 1989; Hall and Hofer, 1993; Cummings, 2008; Kaplan et al., 2009; Petty and Gruber, 2011). Furthermore, there is even no such thing as uniform investment criteria when it comes to soloists.

Last, the presence of the financial sector, the industry in which the candidate deploys its business, on top of the association rules speaks by itself. It is not a capital structure element, of course, but it is not a human capital characteristic either. Thus, only capital structure components plus an economy sector may suffice for convincing program managers of the good prospects of the investment, which would be aligned with the theoretically subsequent fund-raising stages, angels (when in groups, mainly), and venture capitalists.

That said, there is still room for human capital dimensions when properly combined. Higher education is almost ubiquitous, and tenure, work experience in general, is also relevant. Thus, we may say that the role of the entrepreneurs themselves is much appreciated too provided it comes with the appropriate financial backing attached, which may suggest a sort of sequence. First, a financially endorsed business. Second, able entrepreneurs for taking proper care of it.

When previous participation in other programs also appears at the top of the list, either on isolation or alloyed with higher education, this entails further support for the human endowment. The accrued experienced by entrepreneurs in former programs is not transferable and that attribute would also signal the coachability of the team. The role of human capital is indirectly reinforced too when we consider firms which raised philanthropic investment thanks to the presumed personal commitment of the founders with respect to their mission-driven goals.

However, if accelerators preferably bet on the horse for risk-amelioration purposes, the risk profile of those bets raises further questioning because they are utterly disparate. In our first unveiled profile, we see that loan-backed firms are much older, with more senior founders, less educated, with more work experience but lower founding background, and deploy more conservative business models. Apparently, those start-ups do not match the cliché of a rapidly scalable sought-after venture. That image would rather correspond to the second profile, angel-funded firms. Thus, do accelerators select the presumably more conservative loan-backed firms as risk diluters and the apparently riskier angel-backed firms as return enhancers in the same portfolio? Would this be consistent with the proclaimed "spray and pray" investment strategy by accelerators (Ewens et al., 2017)? We would affirm the opposite. If both types of start-ups were selected by the same program, this could denote a rational portfolio diversification to some extent. Another answer to those questions may come from the incentive that accelerators might have for not disclosing negative results (Kim and Wagman, 2014). The need for hype at harvest time may prompt the creation of side pockets for hiding failures while, at the same time, may force the pursuance of allegedly less promising ventures too, the conservative but stable loan-backed firms, for portfolio rebalancing.

However, the presence of such manifestly dissimilar profiles also suggests the existence of at least two distinguishable accelerator types, which could be linked to their quality. As early as 2013, it was already denounced that there was an excessive number of programs and the real capacity of many of them for serving their purpose was being openly questioned (Chang, 2013; Fehder and Hochberg, 2014; Regmi et al., 2015). Therefore, abler programs, accelerators which could bring together seasoned mentors, get exposure to true follow-on investors, and facilitate other services, would invest in riskier start-ups, i.e., angel-funded firms, in hopes of reaping a commensurate return, whereas the others would allocate their monies to hypothetically safer bets, which could guarantee the programs' survival in exchange for lower returns.

Another interesting question accentuated by our research is the fact already cited by the literature (Pierrakis and Owen, 2020) about angel-backed firms applying to programs. This, as mentioned by those scholars, seems a reversal of the sequence of the commonly accepted path for the financing cycle in the life of young and fast-growing firms. Why would a start-up which already sourced funds from an angel investor apply to a program? 1,254 firms (7.63% of the applicants) had already raised equity from business angels at the time of application. That could sound more logical for indebted firms because banks act as mere suppliers of funds. They do not provide any other services. In contrast, business angels are expected to help their investees through the above mentioned value-added services plus, sometimes, even their personal involvement. The answer to this puzzle could come from scholarship again when the literature asserts (Shane, 2009) that lone angels cannot offer real expertise most times. It could also be that some business angels, conscious of their own limitations, cleverly condition additional financing to program participation.

Last, do accelerators choose start-ups or it is candidates who self-select? Cressy (1996a) affirms that there is no credit rationing for start-ups and that they self-select according to their human capital endowment, with abler teams more likely to take out loans from banks. In contrast, Astebro and Bernhardt (2003) contend the opposite, evidence of self-selection against bank loans. More talented teams would prefer another financing rather than loans from banks. The relevance of this comparison comes from the fact that those researchers base their conclusions on the same element, the skills of the teams. When we transfer this framework to our study, what we see, in the absence of a matching sample with start-ups that did not apply to programs, is that different skilled teams depict different capital structures, which is fully consistent with what is claimed in the literature (Cole and Sokolyk, 2013; Cotei and Farhat, 2017), but they all apply to programs. Therefore, we cannot find evidence of self-selection. It is programs who choose ventures.

8.2 Contributions to Theory and Practice

Early stage-financing pivots around the two widely acknowledged propositions earlier mentioned in our review of the literature, Pecking Order Theory of Myers and Majluf (1984), and the Financial Growth Cycle by Berger and Udell (1998). When we address the former, we cannot extrapolate further unconditional support or refusal for it from our research since we have found that successful candidates sported either outside debt or equity on their respective balance sheets at the moment of application. We could at best suggest a certain reversal of that pecking order to some extent, which would be aligned with a scholarship current (Robb and Robinson, 2014; Hechavarria et al., 2016; Pierrakis and Owen, 2020). Firms with angel endorsement are ostensibly younger, and the standard deviation of their average revenues since foundation is much higher than that of their debt counterparts, a 5X relationship. This suggests a higher degree of informational asymmetry, at first, but we have also seen that it has not prevented them from raising outside equity in the end. It is worth remembering at this point that ventures with angels on board are also more popular in our sample, 1,254 firms versus 786, as earlier mentioned.

About the latter, Berger and Udell (1998) argue that the capital structure of firms transitions from inside financing to outside funding as the opacity degree of the venture relaxes, although they themselves also contend that their posited financial growth cycle may not fit well all types of ventures. The evidence in our work points to an absence of a perfectly defined financing growth cycle because the successful candidates had already raised outside financing, either debt or equity, when facing program screening. In sum, we cannot see a clear pattern for giving absolute support or for debunking the just discussed pecking order and growth cycle theories.

In contrast, in addition to unveiling for the first time thorough start-up contours along with the preference of accelerators for debt-backed companies, we can also see that utterly disparate founder teams shape distinct capital structures in the firms they manage. Cole and Sokolyk (2013), Coleman et al. (2016), and Cotei and Farhat (2017), had already pointed out that the personal characteristics of the entrepreneurs, such as their education and working experience, condition the financing mixture of their start-ups. Their findings address the relationship between internal personal debt and external formal debt, mainly. However, we go a step further and reveal the connection between thorough entrepreneur profiles, woven with attributes amply acknowledged by scholarship, and types of outside funding principally. This matching is even reinforced by the fact that equity financing and bank debt hardly ever appear together in our data.

On the other hand, our contributions to the practitioner arena are also important. Entrepreneurs trying to join programs can now know what they first look at, which is not a trivial matter. Entrepreneurs may waste a considerable amount of energy and they may also unintentionally neglect their businesses during the fund-raising process (Hall and Hofer, 1993) precisely because of the shift of their lenses, from the day-to-day deployment of their business plans to the go knocking from door to door until they find someone who is receptive. Our findings are also useful for program sponsors, especially for those either hybrid or publicly-funded, because they may have now a much clearer picture of the relationship between talent and financing in applicants, they may now know better to whom they are lending their resources.

8.3. Limitations and Suggestions for Further Research

The main limitation of this study derives from the absence of information on the nature of the accelerators featured in the database. We do not know anything about the sponsors of those programs, but we consider than information essential for fully understanding their selection criteria. The database informs on whether those programs have got a specific impact area but that can by no means be a reliable indicator of their stance before candidates. The arguments that support this view are, on the one hand, the fact that the social or environmental motives of the candidates is irrelevant. Accelerators in our sample seem not to care. On the other, the for-profit legal status of applicants along with their stated profit goals are two of the most relevant isolated factors in the analyses. Thus, we believe that if we knew who the promoters of the programs are, the selection criteria would be thoroughly understood. Consequently, we encourage further research in this line.

References

Achleitner, A.-K., Lutz, E., Mayer, J., & Spiess-Knafl, W. (2013). Disentangling Gut Feeling: Assessing the Integrity of Social Entrepreneurs, *International Journal of Voluntary and Nonprofit Organizations,* 24(1), 93–124. https://doi.org/10.1007/s11266-012-9264-2

Agrawal, A., Gans, J., Goldfarb, A. (2019). Exploring the Impact of Artificial Intelligence: Prediction versus Judgment. *Information Economics and Policy*, 47(), 1-6. https://doi.org/10.1016/j.infoecopol.2019.05.001

Agrawal, R., Imielinsky, T., Swami, A. (1993). Mining Association Rules between Sets of Items in Large Databases. *ACM SIGMOD International Conference on Management of data*, 207–216. Retrieved 14 April 2022 from https://dl.acm.org/doi/abs/10.1145/3012071.3012097

Agrawal, R., Srikant, R. (1994). Fast Algorithms for Mining Association Rules. *Proc. 20th Int. Conf. Very Large Data Bases VLDB. 1215*. Retrieved 25 April 2022 from https://www.researchgate.net/publication/2460430_Fast_Algorithms_for_Mining_Association_Rules

Ahmad, S., Hermayen, A., Bhavani, G. (2021). Knowledge Discovery in Surveys using Machine Learning: A Case Study of Women in Entrepreneurship in UAE. *Paper presented to the International Conference on Computational Intelligence and Knowledge Economy (ICCIKE)*, 514-518. DOI: 10.1109/ICCIKE51210.2021.9410798.

Allison, P. (2000). Multiple Imputation for Missing Data: A Cautionary Tale. *Sociological Methods & Research*, 28(3), 301-309. https://doi.org/10.1177/0049124100028003003

Atherton, A. (2010). Cases of Start-up Financing. An analysis of New Venture Capitalisation Structures and Patterns. *International Journal of Entrepreneurial Behaviour & Research*, 18(1), 26-47. DOI 10.1108/13552551211201367

Amaral, A., Baptista, R., & Lima, F. (2011). Serial Entrepreneurship: Impact of Human Capital on Time to Re-entry. *Small Business Economics*, 37(1), 1–21. https://doi.org/10.1007/s11187-009-9232-4

Arora, A., & Nandkumar, A. (2011). Cash-out or flame-out! Opportunity Cost and Entrepreneurial Strategy: Theory and Evidence from the Information Security Industry. *Management Science*, 57(10), 1844–1860. https://doi.org/10.1287/mnsc.1110.1381

Astebro, T., Bernhardt, I. (2003). Start-up Financing, Owner Characteristics, and Survival. *Journal of Economics and Business*, 55(4), 303–319. https://doi.org/10.1016/S0148-6195(03)00029-8

Azevedo, P., Alípio, J. (2007). Comparing Rule Measures for Predictive Association Rules. ECML Proceedings of the 18th European conference on Machine Learning. 510-517. Retrieved 10 May 2022 from https://link.springer.com/chapter/10.1007/978-3-540-74958-5_47

Azoulay, P., Jones, B., Kim, J., & Miranda, J. (2020). Age and High-Growth Entrepreneurship. *American Economic Review: Insights*, 2(1), 65–82. DOI: 10.1257/aeri.20180582

Balsmeier, B., Czarnitzki, D. (2014). How Important is Industry-Specific Managerial Experience for Innovative Firm Performance? *ZEW, Centre for European Economic Research. Discussion Paper No. 14-011*. Retrieved 11 January 2021 from https://www.econstor.eu/handle/10419/91726

Baptista, R., Karaöz, M. & Mendonça, J. (2014) The impact of human capital on the early success of necessity versus opportunity-based entrepreneurs. *Small Business Economics*, 42(4), 831–847. https://doi.org/10.1007/s11187-013-9502-z

Barney, J. (1991). Firm Resources and Sustainable Competitive Advantages. *Journal of Management*, 17(1), 99-120. https://doi.org/10.1177/014920639101700108

Bates, T. (1990). Entrepreneur Human Capital Inputs and Small Business Longevity. *The Review of Economics and Statistics*, 72(4), 551-559. https://doi.org/10.2307/2109594

Beaton, E.E. (2021). No Margin, No Mission: How Practitioners Justify Nonprofit Managerialization. *Voluntas: International Journal of Voluntary and Nonprofit Organizations*, 32(), 695–708. https://doi.org/10.1007/s11266-019-00189-2

Beck, T., Demirgüç-Kunt, A., Martínez, M.S. (2011). Bank Financing for SMEs: Evidence Across Countries and Bank Ownership Types. *Journal of Financial Services Research*, 39(1-2), 35–54.

Berger, A., Udell, G. (1998). The economics of small business finance: The roles of private equity and debt markets in the financial growth cycle. *Journal of Banking & Finance*, 22(6-8), 613-673. https://doi.org/10.1016/S0378-4266(98)00038-7

Bernstein, S., Giroud, X., Townsend, R. (2016). The Impact of Venture Capital Monitoring. *The Journal of Finance*, 71(4), 1591-1622. https://doi.org/10.1111/jofi.12370

Bernstein, S., Korteweg, A., Kevin, L. (2016). Attracting Early-Stage Investors: Evidence from a Randomized Field Experiment. *The Journal of Finance*, 72(2), 509-538. https://doi.org/10.1111/jofi.12470

Bertoni, F., Colombo, M., Grilli, L. (2011). Venture Capital Financing and the Growth of High-Tech Start-ups: Disentangling Treatment from Selection Effects. *Research Policy*, 40(7), 1028-1043. https://doi.org/10.1016/j.respol.2011.03.008

Blau, B., Fuller, K. (2008). Flexibility and Dividends. *Journal of Corporate Finance*, 14(2), 133-152. https://doi.org/10.1016/j.jcorpfin.2008.02.003

Bruhn, M., Karlan, D., Schoar, A. (2010). What Capital is Missing in Developing Countries? *American Economic Review*, 100(2), 629–633. DOI: 10.1257/aer.100.2.629

Cassar, G. (2014). Industry and Startup Experience on Entrepreneur Forecast Performance in New Firms. *Journal of Business Venturing*, 29(1), 137-151. https://doi.org/10.1016/j.jbusvent.2012.10.002

Chang, C. (2013). Portfolio Company Selection Criteria: Accelerators vs Venture Capitalists. *CMC Senior Theses. Paper 566*. Retrieved 6 February 2020 from https://scholarship.claremont.edu/cmc_theses/566/

Chen, T., Liu, J., Tu, X. (2021). Extending the Mann-Whitney-Wilcoxon Rank Sum Test to Survey Data for Comparing Mean Ranks. *Statistics in Medicine*, 40(7), 1705-1717. https://doi.org/10.1002/sim.8865
Clarysse, B., Wright, M., Hove, J.V. (2016). A look inside accelerators in the United Kingdom: Building technology businesses. *Technology Entrepreneurship and Business Incubation: Theory, Practice, Lessons Learned*, 57-86. World Scientific Publishing Co. Pte. Ltd.

Cohen, S., Hochberg, Y. (2014). Accelerating Startups: The Seed Accelerator Phenomenon. Retrieved 14 February 2021 from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2418000

Cole, R.A., Sokolyk, T. (2013). How Do Start-Up Firms Finance Their Assets? Evidence from the Kauffman Firm Surveys. Working Paper, Depaul University. Retrieved 7 March 2022 from https://wwws.law.northwestern.edu/research-faculty/clbe/events/innovation/documents/cole-sokolyk_2013-05-28.pdf

Coleman, S., Cotei, C., Farhat, J. (2016). The debt-equity financing decisions of U.S. start-up firms. *Journal of Economics and Finance*, 40(1), 105–126. DOI: 10.1007/s12197-014-9293-3

Colombo, O. (2020). The Use of Signals in New-Venture Financing: A Review and Research Agenda. *Journal of Management*, Vol. 47(1), January 2021, pp. 237–259. DOI: 10.1177/0149206320911090

Colombo, M., Delmastro, M., Grilli, L. (2004). Entrepreneurs' Human Capital and the Start-up Size of New Technology-Based Firms. *International Journal of Industrial Organization*, 22(8–9), 1183-1211. https://doi.org/10.1016/j.ijindorg.2004.06.006

Connelly, B., Trevis Certo, S., Duane, R., Reutzel, C. (2011). Signaling Theory: A Review and Assessment. *Journal of Management*, 37(1), 39-67. https://doi.org/10.1177/0149206310388419

Conti, A., Thursby, M., Rothaermel, F. (2013). Show me the Right Stuff: Signals for High-Tech Startups. *Journal of Economics and Management Strategy*, 22(2), 341-364. DOI: 10.1111/gems.2013.22.issue-2

Cooper, A., Woo, C., Dunkelberg, W. (1998). Entrepreneurs' Perceived Chances for Success. *Journal of Business Venturing*, 3(2), 97-108. https://doi.org/10.1016/0883-9026(88)90020-1

Cosh, A., Cumming, D., Hughes, A. (2009). Outside entrepreneurial capital. *The Economic Journal*, 119(540), 1494–1533. https://doi.org/10.1111/j.1468-0297.2009.02270.x

Cotei, C., Farhat, J. (2017). The Evolution of Financing Structure in U.S. Startups. *The Journal of Entrepreneurial Finance*, 19(1), 1-32. Retrieved 14 March 2022 from https://digitalcommons.pepperdine.edu/cgi/viewcontent.cgi?article=1307&context=jef

Cressy, R. (1996a). Are Business Startups' Debt-Rationed? *The Economic Journal*, 106(438), 1253-1270. https://doi.org/10.2307/2235519

Cressy, R. (1996b). Pre-entrepreneurial income, cash-flow growth, and survival of startup businesses: Model and tests on U.K. data. *Small Business Economics*, 8(1),49-58. https://doi.org/10.1007/BF00391975

Cumming, D. (2008). Contracts and Exits in Venture Capital Finance. *The Review of Financial Studies*, 21(5), 1947–1982. https://doi.org/10.1093/rfs/hhn072

Dass, N., Omesh, K., Nanda, V., Onal, B., Wang, J. (2014). Board Expertise: Do Directors from Related Industries Help Bridge the Information Gap? *The Review of Financial Studies*, 27(5), 1533–1592. https://doi.org/10.1093/rfs/hht071

Davidsson, P., Honig, B. (2003). The Role of Social and Human Capital among Nascent Entrepreneurs. *Journal of Business Venturing*, 18(3), 301 – 331. https://doi.org/10.1016/S0883-9026(02)00097-6

DeGennaro, R. (2010). Angel Investors and their Investments. Retrieved 24 May 2020 from http://dx.doi.org/10.2139/ssrn.1784489

Del Sarto, N., Isabelle, D., Di Minina, A. (2020). The Role of Accelerators in Firm Survival: An fsQCA Analysis of Italian Startups. *Technovation*, 90–91(), 102102. https://doi.org/10.1016/j.technovat ion.2019.102102

Delmar, F., Shane, S. (2006). Does Experience Matter? The Effect of Founding Team Experience on the Survival and Sales of Newly Founded Ventures. *Strategic Organization*, 4(3), 215-247. https://doi.org/10.1177/1476127006066596

Dencker, J., Gruber, M. (2015). The Effects of Opportunities and Founder Experience on New Firm Performance. *Strategic Management Journal*, 36(7), 1035-1052. https://doi.org/10.1002/smj.2269

Dimov, D. (2017). Towards a Qualitative Understanding of Human Capital in Entrepreneurship Research. *International Journal of Entrepreneurial Behaviour & Research*, 23(2), 210-227. https://doi.org/10.1108/IJEBR-01-2016-0016

Dutt, N., Hawn, O., Vidal, E., Chatterji, A., McGahan, A., Mitchell, W. (2016). How Open System Intermediaries Address Institutional Failures: The Case of Business Incubators in Emerging-Market Countries. *Academy of Management Journal*, 59(3), 818-840. http://dx.doi.org/10.5465/amj.2012.0463

Dvouletý, O., Longo, M.C., Blažková, I., Lukeš, M., Andera, M. (2018). Are publicly funded Czech incubators effective? The comparison of performance of supported and non-supported firms. *European Journal of Innovation Management*, 21(4), 543-563. https://doi.org/10.1108/EJIM-02-2018-0043

Ebbers, J., Wijnberg, N. (2012). Nascent ventures competing for start-up capital: Matching reputations and investors. *Journal of Business Venturing*, 27(3), 372-384. https://doi.org/10.1016/j.jbusvent.2011.02.001

Ebrahim, A., Battilana, J., Mair, J. (2014). The Governance of Social Enterprises: Mission Drift and Accountability Challenges in Hybrid Organizations. *Research in Organizational Behavior*, 34(), 81-100. https://doi.org/10.1016/j.riob.2014.09.001

Estrin, S., Mickiewicz, T., Stephan, U. (2016). Human Capital in Social and Commercial Entrepreneurship. *Journal of Business Venturing*, 31(), 449-467. https://doi.org/10.1016/j.jbusvent.2016.05.003

Ewens, M., Nanda, R., Rhodes-Kropf, M. (2018). Cost of experimentation and the evolution of venture capital. *Journal of Financial Economics*, 128(3), 422-442. DOI.org/10.1016/j.jfineco.2018.03.001

Fadil, N., St-Pierre, J. (2021). Growing SMEs and Internal Financing: The Role of Business Practices. *Journal of Small Business and Enterprise Development*, 28(7), 973-994. https://doi.org/10.1108/JSBED-11-2019-0375

Fehder, D., Hochberg, Y. (2014). Accelerators and the Regional Supply of Venture Capital Investment. Retrieved 18 March 2021 from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2518668

Fehder, D., Hochberg, Y. (2018). *Can accelerators accelerate local high-growth entrepreneurship? Evidence from venture-backed startup activity*. Retrieved 10 February 2021 from https://www.semanticscholar.org/paper/Can-Accelerators-Accelerate-Local-High-Growth-from-Fehder/efc6c15e9b2b8ab932bada40f0db6c5fdb50fd3f

Ferrati, F., Muffatto, M. (2021). Entrepreneurial Finance: Emerging Approaches Using Machine Learning and Big Data, *Foundations and Trends in Entrepreneurship*, 17(3), 232-329. http://dx.doi.org/10.1561/0300000099

Fisher, G., Kuratko, D., Bloodgood, J., Hornsby, J. (2017). Legitimate to whom? The challenge of audience diversity and new venture legitimacy. *Journal of Business Venturing*, 32(1), 52-71. https://doi.org/10.1016/j.jbusvent.2016.10.005

Fragkiskos, A., Krasotkina, O., Spilker III, H., Wermers, R. (2022). Private Equity Fund Performance: A Time-Series Approach. Retrieved 2 February 2022 from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3367079

Gilbert-Saad, A., Siedlok, F., McNaughton, R. B. (2018). Decision and design heuristics in the context of entrepreneurial uncertainties. *Journal of Business Venturing Insights*, 9(), 75-80. https://doi.org/10.1016/j.jbvi.2018.02.006

Gimeno, J. Folta, T., Cooper, A., Woo, C. (1997*).* Survival of the Fittest? Entrepreneurial Human Capital and the Persistence of Underperforming Firms. *Administrative Science Quarterly*, 42(4), 750-783. https://doi.org/10.2307/2393656

Goldfarb, B., Hoberg, G., Kirsch, D., Triantis, A. (2009). Does Angel Participation Matter? An Analysis of Early Venture Financing. Retrieved 8 February 2022 from http://guests.angelcapitalassociation.org

Goldfarb, B., Hoberg, G., Kirsch, D., Triantis, A., Triantis. (2013). Are Angels Different? An Analysis of Early Venture Financing. Robert H. Smith School of Business Research Paper No. RHS 06-072. http://dx.doi.org/10.2139/ssrn.1024186. Retrieved 12 March 2022 from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1024186

Golej, R. (2020). Identification the Determinants of Pre-revenue Young Enterprises Value. In: Hernes, M., Wojtkiewicz, K., Szczerbicki, E. (eds) Advances in Computational Collective Intelligence. ICCCI 2020. *Communications in Computer and Information Science*, 1287(). https://doi.org/10.1007/978-3-030-63119-2_31

Gonzalez-Uribe, J., Leatherbee, M. (2018). The Effects of Business Accelerators on Venture Performance: Evidence from Start-Up Chile. *The Review of Financial Studies*, 31(4), 1566-1603. https://doi.org/10.1093/rfs/hhx103

Gorman, M., Sahlman, W. (1989). What do venture capitalists do? *Journal of Business Venturing*, 4(4), 233-248. https://doi.org/10.1016/0883-9026(89)90014-1

Gottschalk, S., Greene, Francis J., Höwer, D., Müller, B. (2014). If you don't succeed, should you try again? The role of entrepreneurial experience in venture survival. *ZEW Discussion Papers* 14-009, ZEW Leibniz Centre for European Economic Research.

Graham, J., Harvey, C. (2001). The Theory and Practice of Corporate Finance: Evidence from the Field. *Journal of Financial Economics*, 60(2-3), 187-243. https://doi.org/10.1016/S0304-405X(01)00044-7

Guo, B., Peng, S. (2020). Do Non-Profit and For-Profit Social Enterprises Differ in Financing? *International Journal of Voluntary and Nonprofit Organizations*, 31(3), 521-532. DOI:10.1007/s11266-020-00218-5

Hahn, E. D. & Soyer, R. (2005*).* Probit and Logit Models: Differences in the Multivariate Realm. *The Journal of the Royal Statistical Society*, Series B, 1--12. http://dx.doi.org/10.2139/ssrn.3028893

Hall, J., Hofer. C. (1993). Venture Capitalists' Decision Criteria in New Venture Evaluation. *Journal of Business Venturing*, 8(1), 25-42. https://doi.org/10.1016/0883-9026(93)90009-T

Hallen, B., Cohen, S., Bingham, C. (2020). Do Accelerators Work? If so, How? *Organization Science*, 31(2), 378-414. https://doi.org/10.1287/orsc.2019.1304

Hamoud, A. (2017). Applying Association Rules and Decision Tree Algorithms with Tumor Diagnosis Data. *International Research Journal of Engineering and Technology*, 3(8), 27-31. http://dx.doi.org/10.2139/ssrn.3028893

Hart, O., Moore, J., (1994). A Theory of Debt Based on the Inalienability of Human Capital. *Quarterly Journal of Economics*, 109(4), 841–879. https://doi.org/10.2307/2118350

Harrison, R., Mason, C., Smith, D. (2015). Heuristics, Learning and the Business Angel Investment Decision-Making Process. *Entrepreneurship & Regional Development*, 27(9-10), 527-554. DOI: 10.1080/08985626.2015.1066875

Harrison, R., Mason, C. (2017). Backing the Horse or the Jockey? Due Diligence, Agency Costs, Information, and the Evaluation of Risk by Business Angel Investors. *International Review of Entrepreneurship*, 15(3), 269-290.

Hechavarria, D., Matthews, C., Reynolds, P. (2016). Does Start-up Financing Influence Start-up Speed? Evidence from the Panel Study of Entrepreneurial Dynamics. *Small Business Economics*, 46(), 137-167. https://doi.org/10.1007/s11187-015-9680-y

Heckman, J.J., Robb, R. (1985). Alternative methods for evaluating the impact of interventions: An overview. *Journal of econometrics*, 30(1), 239-267
Hellmann, T. Puri, M. (2.002). Venture Capital and the Professionalization of Start-up Firms: Empirical Evidence. *The Journal of Finance,* 57(1), 169-197. https://doi.org/10.1111/1540-6261.00419

Hikmawati, E., Maulidevi, N., Surendro, K. (2021). Minimum Threshold Determination Method Based on Dataset Characteristics in Association Rule Mining. *Journal of Big Data*, 8(1). https://doi.org/10.1186/s40537-021-00538-3

Hochberg, Y., Ljungqvist, A., Yang, L. (2007). Whom You Know Matters: Venture Capital Networks and Investment Performance. *The Journal of Finance*, 62(1), 251-301. https://doi.org/10.1111/j.1540-6261.2007.01207.x

Hoffman, D., Radojevich-Kelley, N. (2012). Analysis of Accelerator Companies: An Exploratory Case Study of Their Programs, Processes, and Early Results. *Small Business Institute Journal*, 8(2), 54-70.

Hogan, T., Hutson, E., Drnevich, P. (2017). Drivers of External Equity in Small High-Tech Ventures. *Journal of Small Business Management*, 55(2), 236-253. DOI: 10.1111/jsbm.12270

Honig, B. (2001). Human Capital and Structural Upheaval: A Study of Manufacturing Firms in the West Bank. *Journal of Business Venturing*, 16(6), 575-594. https://doi.org/10.1016/S0883-9026(99)00060-9

Honoré, F. (2020). Joining Forces: How Can Founding Members' Prior Experience Variety and Shared Experience Increase Startup Survival? *Academy of Management Journal*, 65(1), 248-272. https://doi.org/10.5465/amj.2018.1386

Hsu, D. (2004). What do Entrepreneurs Pay for Venture Capital Affiliation? *The Journal of Finance*, 59(4), 1805-1844. https://doi.org/10.1111/j.1540-6261.2004.00680.x

Hsu, D. (2007). Experienced Entrepreneurial Founders, Organizational Capital, and Venture Capital Funding. *Research Policy*, 36(5), 722–741. https://doi.org/10.1016/j.respol.2007.02.022

Hussein, N., Alashqur, A., Sowan, B. (2015). Using the Interestingness Measure Lift to Generate Association Rules. *Journal of Advanced Computer Science & Technology*, 4(1), 156-162. DOI:10.14419/jacst.v4i1.4398

Ibrahim, D. (2010). Debt as Venture Capital. *University of Illinois Law Review*, 2010(), 1169. http://dx.doi.org/10.2139/ssrn.1418148

Jensen, M., Meckling, W. (1976). Theory of the Firm: Managerial Behaviour, Agency Costs, and Ownership Structure. *Journal of Financial Economics*, 3(4), 305-360.

Jensen, M. (1986). Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers. *American Economic Review*, 76(2), 323-329.

Jones, P., Pickernell, D., Fisher, R., Netana, C. (2017). A Tale of Two Universities: Graduates Perceived Value of Entrepreneurship Education. *Education + Training*, 59(7/8), 689-705. https://doi.org/10.1108/ET-06-2017-0079

Jones, S. (2020). Prior CEO Experience as a Predictor of Entrepreneurial IPO Success: An Analysis of VC Investment Performance. Retrieved 25 September 2020 from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3463135

Kambourova Z., Stam E. (2017). Entrepreneurs' Over-optimism During the Early Life Course of the Firm. In Pyka A., Cantner U. (Eds) Foundations of Economic Change. Economic Complexity and Evolution. Springer, Cham. https://doi.org/10.1007/978-3-319-62009-1_15

Kaplan, S., Sensoy, B., Stromberg, P. (2009). Should Investors Bet on the Jockey or the Horse? Evidence from the Evolution of Firms from Early Business Plans to Public Companies. *The Journal of Finance*, 63(4), 1653-1678. https://doi.org/10.1111/j.1540-6261.2008.01429.x

Kerr, W., Lerner, J., Schoar, A. (2014). The Consequences of Entrepreneurial Finance: Evidence from Angel Financings. *The Review of Financial Studies*, 27(1), 20-55. https://doi.org/10.1093/rfs/hhr098

Kim, J. H., Wagman, L. (2014). Portfolio Size and Information Disclosure: An Analysis of Startup Accelerators. *Journal of Corporate Finance*, 29(), 520–534. https://doi.org/10.1016/j.jcorpfin.2014.10.017

Kim, P., Aldrich, H., Keister, L. (2006). Access (Not) Denied: The Impact of Financial, Human, and Cultural Capital on Entrepreneurial Entry in the United States. *Small Business Economics*, 27(1), 5-22. DOI: 10.1007/s11187-006-0007-x

Ko, E.-J., McKelvie, A. (2018). Signaling for more money: The roles of founders' human capital and investor prominence in resource acquisition across different stages of firm development. *Journal of Business Venturing*, 33(), 438–454. https://doi.org/10.1016/j.jbusvent.2018.03.001

Kraus, A., Litzenberger, R. (1973). A State-Preference Model of Optimal Financial Leverage. *The Journal of Finance*, 28(4), 911-922.

La Rocca, M., La Rocca, T., Gerace, D., Smark, C.J. (2009). The Effect of Diversification on Capital Structure. *Accounting & Finance*, 94(4), 799-826. https://ro.uow.edu.au/commpapers/729

Lall, S., Jacob, P. (2020). How Social Ventures Grow: Understanding the Role of Philanthropic Grants in Scaling Social Entrepreneurship, *Business & Society*, 61(1), 3-44. https://doi.org/10.1177%2F0007650320973434

Lall, S. A.; Chen, L.-W., Roberts, P. (2020). Are we accelerating equity investment into impact-oriented ventures? *World Development*, 131(), 104952. https://doi.org/10.1016/j.worlddev.2020.104952

Lafontaine, F., Shaw, K. (2016). Serial Entrepreneurship: Learning by Doing? *Journal of Labor Economics*. University of Chicago Press, 34(S2), 217-254. https://doi.org/10.1086/683820

Leadbeater, C. (1997). The Rise of the Social Entrepreneur, Demos, London.

Lévesque, M., Minniti, M. (2006). The Effect of Aging on Entrepreneurial Behavior. *Journal of Business Venturing*, 21(2), 177-194. https://doi.org/10.1016/j.jbusvent.2005.04.003

Mackiewicz, M., Kurczewska, A. (2020*).* Is it the survival of the fittest or the jack-of-all-trades? Business Survival in the Light of Lazear's theory. *Business Research Quarterly*, 1-14. https://doi.org/10.1177/2340944420976652

Mahesh, B. (2020). Machine Learning Algorithms - A Review. *International Journal of Science and Research*, 9(1). DOI: 10.21275/ART20203995
Mansoori, Y., Karlsson, T., Lundqvist, M. (2019). The influence of the lean startup methodology on entrepreneur-coach relationships in the context of a startup accelerator, *Technovation*, 84–85(), 37-47. https://doi.org/10.1016/j.technovation.2019.03.001

Markova, S., Petkovska-Mircevska, T. (2009). Financing Options for Entrepreneurial Ventures. *The AMFITEATRU ECONOMIC Journal*, 11(26), 597-604.

Marvel, M., Davis, J., Sproul, C. (2016*). Human Capital and Entrepreneurship Research: A Critical Review and Future Directions*. *Entrepreneurship Theory and Practice,* 40(3), 599-626. https://doi.org/10.1111/etap.12136

Mason, C., Stark, M. (2004). What do Investors Look for in a Business Plan? A Comparison of the Investment Criteria of Bankers, Venture Capitalists and Business Angels. *International Small Business Journal*, 22(3), 227–248

Mincer, J. (1958). Investment in Human Capital and Personal Income Distribution. *Journal of Political Economy*, 66 (4), 281-302. https://doi.org/10.1086/258055

Miranda, B., Amorim, V., Kimura, H. (2019). Literature review: Machine learning techniques applied to financial market prediction. *Expert Systems with Applications*, 124(), 226-251. Https://doi.org/10.1016/j.eswa.2019.01.012.

Modigliani, F., Miller, M. (1958). The Cost of Capital, Corporation Finance and the Theory of Investment. *The American Economic Review*, 48(3), 261-297

Modigliani, F., Miller, M. (1963). Corporate Income Taxes and the Cost of Capital: A Correction. *The American Economic Review*, 53(3), 433-443

Myers, S., Majluf, N. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, 13(2), 187-221.

Nahata, R. (2020). Success is good but failure is not so bad either: Serial entrepreneurs and venture capital contracting. *Journal of Corporate Finance*, 58(), 624-649. https://doi.org/10.1016/j.jcorpfin.2019.07.006

Nasution, M., Siahaan, A., Rossanty, Y., Lubis, S. (2018). Entrepreneurship Intention Prediction using Decision Tree and Support Vector Machine. ICAI'18: Proceedings of the Joint Workshop KO2PI and the 1st International Conference on Advance & Scientific Innovation. 135–148. https://doi.org/10.4108/eai.23-4-2018.2277587

Nielsen, K. (2015). Human capital and new venture performance: The industry choice and performance of academic entrepreneurs. *Journal of Technology Transfer*, 40(), 453–474. https://doi.org/10.1007/s10961-014-9345-z

Obisi, C., Anyim, F. (2012). Developing The Human Capital for Entrepreneurship challenges and successes. *International Journal of Academic Research in Business and Social Sciences*, 2(3), 51-58.

Ordonez, C. (2011). Evaluating association rules and decision trees to predict multiple target attributes. *Intelligent Data Analysis*, 15(2), 173-192. DOI: 10.3233/IDA-2010-0462

Penrose, E.T. (1959). The Theory of the Growth of the Firm. *Oxford: Oxford University Press*. Also available in 2009 as the 4th edition

Peña, I. (2004). Business Incubation Centers and New Firm Growth in the Basque Country. *Small Business Economics*, 22(3/4), 223-236. https://doi.org/10.1023/B:SBEJ.0000022221.03667.82

Petty, J., Gruber, M. (2011). "In Pursuit of the Real Deal": A Longitudinal Study of VC Decision Making. *Journal of Business Venturing*, 26(2), 172-188. https://doi.org/10.1016/j.jbusvent.2009.07.002

Pierrakis Y., Owen, R. (2020). Accelerating green ventures: an exploration of how young environmental ventures signal a green light to their accelerator investors. Paper presented to the Institute for Small Business and Entrepreneurship (ISBE) online conference: SME Finance for Building Back Better, ISBE, 1-2 June 2020

Prasad, D., Bruton, G., Vozikis, G. (2000). Signaling value to business angels: the proportion of the entrepreneur's net worth invested in a new venture as a decision signal. *Venture Capital*, 2(3), 167-182. https://doi.org/10.1080/13691060050135064

Rahman, A., Zbrankova, H. (2019). Female Borrowers and Credit Constraints in SME Loan market: An Analyses from the Visegrad Countries. *Polish Journal of Management Studies*, 20(2), 426-440. https://doi.org/10.17512/pjms.2019.20.2.36

Ratzinger, D., Amess, K., Greenman, A., Mosey, S. (2018). The Impact of Digital Start-up Founders' Higher Education on Reaching Equity Investment Milestones. *The Journal of Technology Transfer*, 43 (), 760–778. https://doi.org/10.1007/s10961-017-9627-3

Regmi, K., Ahmed, S. A., Quinn, M. (2015). Data Driven Analysis of Startup Accelerators. *Universal Journal of Industrial and Business Management*, 3(2), 54-57. DOI: 10.13189/ujibm.2015.030203

Rekik, R., Kallel, I., Casillas, J., Alimi, A. (2018). Assessing Web Sites Quality: A Systematic Literature Review by Text and Association Rules Mining. *International Journal of Information Management*, 38(1), 201-216. DOI: 10.1016/j.ijinfomgt.2017.06.007

Reynolds, P. (2011). Informal and Early Formal Financial Support in the Business Creation Process: Exploration with PSED II Data Set. *Journal of Small Business Management*, 49(1), 27–54.

Rich, N. (2013). Silicon Valley's Start-Up Machine. Retrieved 8 February 2021 from https://archive.nytimes.com/www.nytimes.com/2013/05/05/magazine/y-combinator-siliconvalleys-start-up-machine.html

Rider, C., Thompson, P., Kacperczyk, A., Tåg, J. (2019). Experience and Entrepreneurship: A Career Transition Perspective. *ILR Review*, 72(5), 1149-1181. https://doi.org/10.1177/0019793919852919

Robb, A., Robinson, D. (2014). The Capital Structure Decisions of New Firms. *The Review of Financial Studies*, 27(1), 153–179. https://doi.org/10.1093/rfs/hhs072

Ross, S. (1977). The Determination of Financial Structure: The Incentive-Signalling Approach. *The Bell Journal of Economics*, 8(1), 23-40.

Sabahi, S., Parast, M. (2020). The impact of entrepreneurship orientation on project performance: A machine learning approach. *International Journal of Production Economics*, 226(C). https://doi.org/10.1016/j.ijpe.2020.107621.

Samuelsson, M., Davidson, P. (2009). Does Venture Opportunity Variation Matter? Investigating Systematic Process Differences between Innovative and Imitative New Ventures. *Small Business Economics*, 33(), 229–255. https://doi.org/10.1007/s11187-007-9093-7

Sánchez-Vidal, J., Martín-Ugedo, J.F. (2012). Are the Implications of the Financial Growth Cycle Confirmed for Spanish SMEs? *Journal of Business Economics and Management*, 13(4), 637-665. doi:10.3846/16111699.2011.620161

Scarlata, M., Zacharakis, A., Walske, J. (2016). The Effect of Founder Experience on the Performance of Philanthropic Venture Capital Firms. *International Small Business Journal*, 34(5), 618-636. DOI: 10.1177/0266242615574588

Serrasqueiro, Z., Caetano, A. (2015). Trade-Off Theory versus Pecking Order Theory. Capital Structure Decisions in a Peripheral Region of Portugal. *Journal of Business Economics and Management*, 16(2), 445-466. doi:10.3846/16111699.2012.744344

Shane, S. (2005). Angel Investing: A Report Prepared for the Federal Reserve Banks of Atlanta, Cleveland, Kansas City, Philadelphia and Richmond. http://dx.doi.org/10.2139/ssrn.1142687. Retrieved 10 April 2022 from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1142687

Shane, S. (2008). Angel Groups: An Examination of the Angel Capital Association Survey. ttp://dx.doi.org/10.2139/ssrn.1142645. Retrieved 24 April 2022 from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1142645

Shane, S. (2009). Fool's Gold: The Truth Behind Angel Investing in America. (1st ed.). Oxford University Press.

Shane, S., Venkataraman, S. (2000). The Promise of Entrepreneurship as a Field of Research. *The Academy of Management Review*, 25(1), 217-226. https://doi.org/10.5465/amr.2000.2791611

Shaw, E., Carter, S. (2007). Social Entrepreneurship. Theoretical Antecedents and Empirical Analysis of Entrepreneurial Processes and Outcomes, *Journal of Small Business and Enterprise Development*, 14(3), 418-434. DOI 10.1108/14626000710773529

Shaw, K. L., Sørensen, A. (2019). The Productivity Advantage of Serial Entrepreneurs. *Industrial and Labor Relations Review*, 72(5), 1225-1261. https://doi.org/10.1177/0019793919865501

Shepherd, D., Williams, T., Patzelt, H. (2015). Thinking About Entrepreneurial Decision Making: Review and Research Agenda, *Journal of Management*, 41(1), 11–46. DOI: 10.1177/0149206314541153

Shu, C., Simmons, S.A. (2018). Firm survival in traded industries: does localization moderate the effects of founding team experience? *Small Business Economics*, 50(), 643–655. https://doi.org/10.1007/s11187-017-9912-4

Spence, M. 1973. Job Market Signalling, *Quarterly Journal of Economics*, 87(), 355-374.

Staniewski, M. (2016). The contribution of business experience and knowledge to successful entrepreneurship. *Journal of Business Research*, 69(11), 5147-5152. https://doi.org/10.1016/j.jbusres.2016.04.095

Stayton, J., Mangematin, V. (2019). Seed accelerators and the speed of new venture creation. *The Journal of Technology Transfer*, 44(4), 1163-1187. https://doi.org/10.1007/s10961-017-9646-0

Stiglitz, J. E. (2002). Information and the change in the paradigm in economics. *American Economic Review*, 92(), 460-501. DOI: 10.1257/00028280260136363

Stucki, T. (2016). How the Founders' General and Specific Human Capital Drives Export Activities of Start-ups. *Research Policy*, 45(5), 1014-1030. https://doi.org/10.1016/j.respol.2016.02.010

Tangirala, S. (2020). Evaluating the Impact of GINI Index and Information Gain on Classification using Decision Tree Classifier Algorithm. *International Journal of Advanced Computer Science and Applications*, 11(2). DOI:10.14569/IJACSA.2020.0110277

Tian, X., (2011). The causes and consequences of venture capital stage financing. *Journal of Financial Economics*, 101(1), 132-159. https://doi.org/10.1016/j.jfineco.2011.02.01

Ucbasaran, D., Alsos, G., Westhead, P., Wright, M. (2008). Habitual Entrepreneurs. *Foundations and Trends in Entrepreneurship*, 4(4), 309–450. http://dx.doi.org/10.1561/0300000014

Unger, J., Rauch, A., Frese. M., Rosenbusch, N. (2011). Human capital and entrepreneurial success: A meta-analytical review. *Journal of Business Venturing*, 26(), 341–358. https://doi.org/10.1016/j.jbusvent.2009.09.004

Vaillant, Y., Lafuente, E. (2019). Entrepreneurial experience and the innovativeness of serial entrepreneurs. *Management Decision*, 57(11), 2869-2889. https://doi.org/10.1108/MD-06-2017-0592

Venâncio, A., Jorge, J. (2021). The Role of Accelerator Programmes on the Capital Structure of Startups. *Small Business Economics*, (), https://doi.org/10.1007/s11187-021-00572-8

Waleczek, P., Zehren, T., Flatten, T.C. (2018). Start-up financing: How founders finance their ventures' early stage. *Managerial and Decision Economics*, 39(5), 535-549. https://doi.org/10.1002/mde.2925

Wiltbank, R., Boeker, W. (2007). Returns to Angel Investors in Groups. http://dx.doi.org/10.2139/ssrn.1028592. Retrieved 4 January 2022 from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1028592

Winston-Smith, S., Hannigan, T. (2017). *Home Run, Strike Out, or Base Hit: How Do Accelerators Impact Exit and VC Financing in New Firms?* Retrieved 24 January 2021 from https://www.researchgate.net/publication/276898163_Home_Run_Strike_Out_or_Base_Hit_How_Do_Accelerators_Impact_Exit_and_VC_Financing_in_New_Firms

Winston-Smith, S., Hannigan, T., Gasiorowski, L. (2015). Peering Inside: How do Peer Effects Impact Entrepreneurial Outcomes In Accelerators? *Academy Of Management*, 2015(1). https://doi.org/10.5465/ambpp.2015.1707

Wooldridge, J. (2013). Introductory Econometrics. A modern Approach. (5th Ed.). South-Western. Cengage Learning

Wright, F. (2017). How do entrepreneurs obtain financing? An evaluation of available options and how they fit into the current entrepreneurial ecosystem, *Journal of Business & Finance Librarianship*, 22(3-4), 190-200. DOI: 10.1080/08963568.2017.1372011

Xu, B., Yang, J., Sun, B. (2018). A Nonparametric Decision Approach for Entrepreneurship. *International Entrepreneurship and Management Journal*, 14(1), 5–14. DOI: 10.1007/s11365-017-0465-4

Yang, S., Kher, R. (2018*).* Where Do Accelerators Fit in the Venture Creation Pipeline? Different Values Brought by Different Types of Accelerators. *Baruch College Zicklin School of Business*. Research Paper No. 2018-07-02. http://dx.doi.org/10.2139/ssrn.3212379

Yang, S., Kher, R., Newbert, S. (2020). What signals matter for social startups? It depends: The influence of gender role congruity on social impact accelerator selection decisions. *Journal of Business Venturing*, 33(2), 105932. https://doi.org/10.1016/j.jbusvent.2019.03.001

Ye, Q. (2017). Bootstrapping and New-born Startups Performance: The Role of Founding Team Human Capital, *Global Journal of Entrepreneurship*, 1(2), 53-71

Yitshaki, R., Kropp, F. (2016). Motivations and Opportunity Recognition of Social Entrepreneurs. *Journal of Small Business Management*, 54(2), 546-565. DOI: 10.1111/jsbm.12157

Yu, S. (2019). How do Accelerators Impact the Performance of High Technology Ventures? *Management Science*, 66(2), 530-552. https://doi.org/10.1287/mnsc.2018.3256

Zhang, S., Cueto, J. (2017). The Study of Bias in Entrepreneurship. *Entrepreneurship Theory and Practice*, 41(3), 419-454. DOI: 10.1111/etap.12212

Zhang, H., Bij, H.v.d., Song, M. (2020). Can cognitive biases be good for entrepreneurs? *International Journal of Entrepreneurial Behavior & Research*, 26(4), 793-813. https://doi.org/10.1108/IJEBR-03-2019-0173

Zingales, L. (2000). In Search of New Foundations. *The Journal of Finance*, 55(4), 1623-1653. https://doi.org/10.1111/0022-1082.00262