

An empirical study of start-up teams funding: the signaling role of skills endorsement

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Abstract

Entrepreneurship research and signaling theory suggest that start-up teams' human capital has a signal-quality effect on how easily they can access financial resource from investors. Based on a sample of 514 software-based firms, we examine the signal effect of skills and expertise endorsement, a peer-reviewed relational measure of professional capabilities, and its influence on the amount of external funding received in early stage. Results show that investors favor start-up teams that have either a high level of competency or a high level of variety of skills, but only some at once. We discuss the implications of these findings for the research literature on digital entrepreneurship and venture capital.

Keywords: Skills, Entrepreneurship, Fundraising, Start-up Teams, Variety

JEL Classification: L22, L26, L85

1 Introduction

Start-up teams, which possess attributes such as equity ownership, decision-making autonomy and entitativity (?), are seen as vital agents in the development of cities, regions and countries, due to their role in the creation of a firm (??). Acquiring financial resources is a key factor in the survival and expansion of start-up teams (?), thus making the determinants and methods of attracting such resources of great interest to researchers, practitioners, and policy makers (?). This is especially relevant in the digital economy, where low-resource-intensive systems offer investors new possibilities since digital technologies can generate non-linear revenues in an efficient, predictable, and repeatable manner (??). This article contributes to the critical agenda by exploring the connection between start-up teams' human capital signals and their performance in a digital environment, paying particular attention to resource access, specifically the access to external capital financing from professional investors.

Which start-up teams are funded by external investors and why are recurring themes in contemporary economic and entrepreneurial literature (????????). Previous studies have largely focused on the individual qualities of founding members, such as education, work experience, and prior entrepreneurial endeavors, in order to explain the acquisition of financial resources by start-up teams (??). While these studies have yielded several important insights, this approach is problematic, as nowadays investors draw on a wide array of other signals to assess the relevance of investing in a start-up team, such as social proof data available on social networks. As this approach has been underexplored by researchers, this research seeks to investigate the signaling role of skills and expertise endorsements—i.e., a peer-reviewed relational measure of professional capabilities—on the ability of start-up teams to acquire fi-

nancial resources from professional investors. Skills and expertise endorsements are a social proof data available on LinkedIn, the world’s largest professional online social network, that allows users to tag themselves with topics representing their area of expertise and have their connections provide social proof of their competence in that topic.

Using data from a sample of 514 software-based ventures listed on Crunchbase and BPI combined with data from LinkedIn, company websites, and press articles, we constructed a unique dataset that includes ”human capital investments” (i.e., common traditional signals used by investors such as years of education, professional experience, and previous founding experience) and ”outcomes of human capital” (i.e., skills and expertise endorsements) of start-up teams (?). We analyze our statement in two stages. First, we examine the relationship between the signal of the level of skills and expertise endorsement of start-up teams and its impact on capital acquisitions in early-stage investment. Secondly, drawing from the cognitive distance model (?) and the cybernetics principles of requisite variety applied to the entrepreneurship literature (??), we assess the extent to which signals from startup teams’ skills and expertise endorsements variety help the firm acquire capital. Following our claims, we find that investors favor start-up teams that have either a high level of competency or a high level of variety of skills, but not both at once.

Our study contributes to the literature on signaling and new venture financing in multiple ways. First, this study presents a new approach to examining the signaling role of the composition of start-up teams (?). Previous research has generally focused on either the proficiency level or variety of skills possessed by start-up teams. However, neither dimension by itself is sufficient to explain the success of the firm.

In addition, the digital context is subject to different social and technological factors requiring a different type of signal-quality by investors and to logics of different natures (?). The proposed methodology evaluates both proficiency and variety of skills simultaneously within this digital context. Second, various empirical studies on the impact of the composition of start-up teams on investors' evaluations have been conducted, taking into consideration indicators such as founders' education (?), entrepreneurial experience (?), industry experience (?), or leadership experience (?). This article proposes a complementary approach, focusing on the 'outcomes of human capital' (i.e. the knowledge, skills and abilities), which are considered to be more precise and direct indicators than those related to 'investment in human capital' such as education and years of experience (??). Methodologically speaking, we derive from a peer-reviewed relational measure an outcome-based human capital indicator and consider it as one approach to analyzing how skills and expertise endorsement affect firms' resource acquisition. Third, this study presents a unique dataset which combines multiple sources of validated data (including Crunchbase, BPI, LinkedIn, company websites and press articles). We make use of CrunchBase and LinkedIn especially, as they provide reliable self-reported information which can accurately capture an individual's human capital trajectories (see previous academic work e.g., ?, ?, or ?). Consequently, this study highlights the data limitations researchers currently face when studying the acquisition of financial resources by firms. Current datasets lack information on both founder characteristics (such as occupation and education) and attributes of small firms (employment size, financial resources). By collecting data from LinkedIn, we have constructed a dataset which covers over 514 start-up teams in France. This paper serves to demonstrate the value of the data for

research, particularly to understand the dynamics of signals in entrepreneurship.

The paper is structured as follows. Section 2 reviews the literature on signaling theory for early-stage resource acquisition. Section 3 explains the data and methods used, and Section 4 presents key findings. Finally, section 5 concludes by discussing implications for theory and practice, noting the limitations of this study.

2 Theoretical framework and hypothesis

2.1 Signaling theory for early-stage resource acquisition

Literature on entrepreneurship has continually underscored the critical role of external financial resources for the survival and growth of new firms (?). Despite the numerous types of external financial sources obtainable to start-up teams (??), the majority of research has concentrated on the acquisition of capital from external investors, who provide financial capital in return for a stake in the company’s ownership. Nevertheless, securing external funding from external investors is a challenging task, with investors having difficulty predicting which teams will come out on top (??), due to the inherent information asymmetries between entrepreneurs and investors or the lack of past financial results. In order to mitigate the information asymmetries, investors draw on quality-signals (??), with signalling theory being particularly applicable in the digital context, where new digital technologies have transformed the nature of uncertainty inherent in entrepreneurial processes (?).

Signaling theory posits that two parties take conscious and voluntary steps to reduce asymmetric information and perceived uncertainty between them, and this is done by focusing on the signals available to them (?). This concept has been used

in various disciplines to provide insight into social selection problems when there is an absence of perfect information (??). Entrepreneurship scholars have found this concept to be beneficial as particular signals can diminish uncertainty about ventures' quality in the eyes of stakeholders, such as prestigious government grants (?), the enthusiasm and passion of the founders (?), affiliations of the venture with other entities (?), and the composition of the founders' team (?). Investors, similarly, use a variety of indicators to mitigate asymmetric information such as the founders' ties to others (?), their human capital (?), social capital (?), and endorsements (???).

In the context of early-stage ventures, human capital of the start-up teams is considered to be a significant and prominent factor for investors to consider (???). This emphasis is due to the limited resources and small number of people responsible for formulating and carrying out strategies. According to the organizational theory perspective applied to the entrepreneurship field, the human capital composition of the start-up teams is believed to have an imprinting effect on the processes and operations of the firm (?). This concept implies that past experiences, and therefore the underlying skills and experiences acquired meanwhile, can shape the present performance. Concretely, investors aim to reduce uncertainty about the quality of the firm by relying on the human capital and demographic characteristics of start-up teams such as their educational background or their functional skills because these are easily accessible quality-signals (???).

Extensive research has been conducted to explore the association between signaling and the acquisition of financial resources (see (?) and ? for a review). However, no studies have examined the signaling role of skills and expertise endorsement - a "social proof data" available on professional social networks - and financial resource

acquisition in the early stages of venture creation. This gap in the literature is remarkable given that the level of uncertainty (?) and information asymmetry between the signal sender and receiver (?) are most pronounced during this period. Therefore, any kind of quality-signals that help gain additional perspective and triangulate start-up teams data is welcomed by investors. At this juncture, a new venture typically has no track record of performance to rely on, yet must still find a way to convince stakeholders that it is a legitimate venture (?), and thus worthy of obtaining necessary resources, such as financial capital (?).

This paper proposes to investigate how investors rely on "social proof data" signals to determine the potential of new firms they are considering investing in. To this end, we will focus on the signal effect of skills and expertise endorsement, a peer-reviewed relational measure of professional capabilities feature on LinkedIn, the world's largest professional online social network. This feature enables members to tag themselves with topics representing their areas of expertise and their connections to provide social proof via the endorsement of said member's competency in the topic.

2.2 Signaling effects from start-up teams' level of skills and expertise endorsement

Entrepreneurship researchers have extensively explored what start-up teams' characteristics enable them to access external funding (?). The focus on start-up teams stems from the fact that most entrepreneurial initiatives are run mainly by groups of individuals rather than by lone individuals (?). Such characteristics include the teams' social capital (?), the team's demographics and size (?), the teams' match with an investor's characteristics (?), the industry environment (?) or the investor's

experience (?). However, in the context of early-stage ventures, human capital of the start-up teams is maybe the most significant and prominent factor for investors to consider (???).

In the literature, skills are considered human capital outcomes and refer to agents' "observable applications or know-how related to a domain" (??). In this study, conformed to the human capital literature applied to the entrepreneurial field, we postulate that start-up teams with higher levels of skills have a greater propensity to reach specific entrepreneurial milestones, elicit greater investor confidence, and a greater likelihood of attracting external financial capital. Indeed, it has been shown that higher levels of skills enable founders to take greater risks and demonstrate proactive behavior (?), allowing them to optimize business opportunities (??). Additionally, the acquired skills enable entrepreneurs to make full use of the available technological tools in a digital context (?), enabling them to better understand and differentiate their offerings through the introduction of new technologies and disruptive products (?). Moreover, a high level of skill proficiency can help entrepreneurs to obtain resources complementary to financial resources, which is an issue for many firms in the early stages of development (??). Finally, developing skills and knowledge is a prerequisite for further entrepreneurial learning and helps business owners acquire additional skills and knowledge that will help their firm grow (?).

Therefore, for all these reasons, we propose that a high level of skills and expertise endorsements within a start-up team enhances the quality of the signal intended for investors looking to engage financially in the early stages. The investors are alerted by this signal because it suggests that higher skill levels may translate into future success. Thus, we hypothesize the following:

H1: Start-up teams with greater skills and expertise endorsement levels will get more fundings from investors

2.3 Signaling effects from start-up teams' variety of skills and expertise endorsement

In this study, we consider not only the level of skills but also their variety (??). Skills' variety in a start-up team matters because the success of entrepreneurial initiatives is often the result of teamwork and collective endeavors, which require the combination of knowledge, the synergy of abilities, and the collaboration of multiple individuals (?). This paper argue that start-up teams with a wide range of skills and expertise endorsement have a greater chance of acquiring investors due to two key reasons.

The first reason relates to the decision-making process. The underlying argument is that groups with various skills take better decisions because they have access to more information (?). Therefore, the solutions to new issues encountered during entrepreneurial cycles might result from recombining existing knowledge under new forms. A meta-analysis conducted by ? suggests that an entrepreneurial teams endowed with a varied skill set are more likely to use various market entry, internationalization or innovation strategies (?). This implies that start-up teams with diverse skills are in a better position to make high-quality decisions, thus increasing their chances of success. Consequently, investors may use start-up teams' skills diversity as a signal to assess their future performance, which can significantly impact the probability of receiving investments.

The second reason related to the connection between start-up teams' skills and

expertise diversity and their social capital. The literature demonstrates that the social capital of a start-up team has the capacity to act as control for information asymmetries. Indeed, ?? posit that the presence of a social connection between start-up teams and investors can reduce the informational gap between them. Specifically, ? infer that social capital play a role in connecting start-up teams to potential investors and facilitating fundraising. Additionally, ? suggest that the social capital of a start-up team is utilized by investors to triangulate the quality of the firm and the composition of start-up teams and their relationships are used as indicators of quality by investors (??). Following these rationales, if a start-up team’s diversity of skills endorsements is the result of different social capital and given that capital influences the start-up teams’ ability to raise funds from investors, start-up teams with diverse skills might therefore raise more funds than less diversified ones. Thus, we hypothesize the following:

H2: Start-up teams with greater skills and expertise endorsement variety will get more fundings from investors

The past two rationales invite us to think that having high both highly skilled individuals and a high levels of variety within a startup team is beneficial for firm performance. However past findings suggest that adding more human capital to a start-up team does not necessarily translate into greater success (?).

Indeed, if empirical studies suggest that a certain level of human capital stimulates the discovery of new business opportunities (??), increases the likelihood of developing radically new and commercially viable products (?), and increases the

odds of securing external funding (?), findings of cognitive and social psychology indicate that highly skilled individuals tend to have higher cognitive rigidity (?). This can be attributed to the fact that long-term exposure to a specific discipline leads to a mentality where solutions and situations are addressed according to the dominant logic paradigm of the discipline. While this cognitive rigidity can lead to greater determination, better products, and improved ability to recognize and take advantage of business opportunities, the perils of cognitive rigidity are both more likely and especially threatening when two or more individuals also have high cognitive distance.

Cognitive distance reflects the extent to which two individuals have developed different mental models, belief systems, vocabularies, and priorities (?). Cognitive distance can impede interaction and communication with other start-up team members and make people less likely to be open to radically different logic, such as pivoting and successfully executing new business alternatives (?). While any two people are always cognitive distant to some extent, individuals who share the same skills and expertises tend to have lower cognitive distance because they are more likely to be familiar with each other's mental models, and to build the mutual trust that is necessary for the effective functioning of a social group. Conversely, individuals who are endowed with completely different skills and expertises are less likely to have similar worldviews, knowledge, which increases their cognitive distance. In turn, this reduces the quality of both their interactions and their decisions, and the ability to interact effectively. Since the negative effects of cognitive distance are more extreme when group members have crystallized mental models and are entrenched in their opinions and positions (i.e., when they are cognitively rigid), start-up teams members who are highly skilled in different

disciplines are less likely to take advantage of the benefits of their broader skill sets, information, and social capital endowments. Thus, we hypothesize the following:

H3: Start-up teams' skill and expertise endorsement variety impact negatively the positive effect of level of skill and expertise endorsement on the funds raised

Our formal hypotheses (H1, H2, H3) conform with the proposed model presented in Figure ??

3 Methodology

3.1 Data sources and collection process

To test our hypotheses, we built a dataset with information on firms, their fundraising activities, and granular information on the skill and expertises of start-up

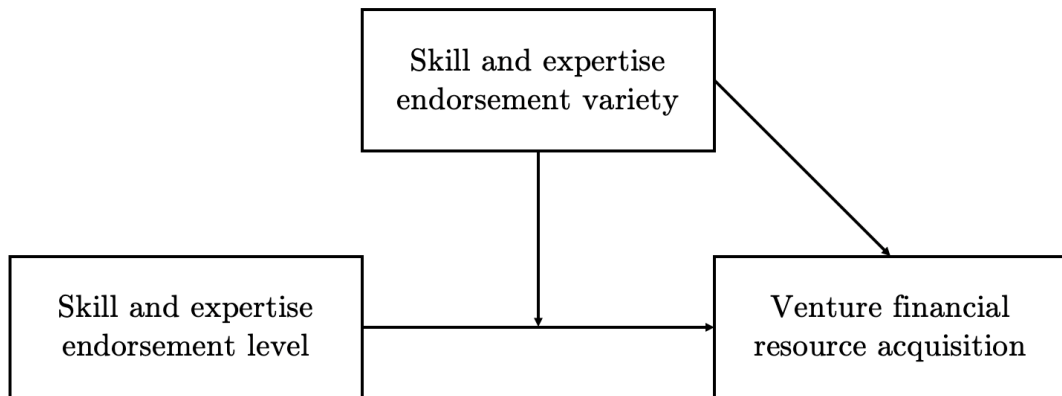


Figure 1: Research Model

teams’ members. Table lists our empirical variables, definitions, and sources. Table provides the general statistics and distribution across sizes and sectors. provides the descriptive statistics of the fundraising activities of the 514 firms in our sample. We detail the collection process below.

INSERT TABLE 1 HERE

First, we draw on Crunchbase and BPI databases as a starting point. These databases provide information on the firm’s headquarters, founders’ names, fundraising activity, business models, and date foundation. We collected this data in March 2020 and kept firms that (i) were founded between 2010 and 2018, (ii) had their headquarters in the Metropolis of Greater Paris (France), (iii) were independent (no subsidiaries), (iv) operate in business to business markets and (v) used digital Software-as-a-Service (SaaS) business models. From these filters, we ended up with 498 SaaS digital firms¹. These criteria were chosen as a way to pinpoint the mechanisms that matter most to start-up teams working a given context. In fact, the dynamics of composition for start-up teams based in other regions may differ significantly; sampling start-up teams from a broad landscape could introduce noise into a focused investigation. Therefore, we could create accurate theoretical models for one particular area (Metropolis of Greater Paris) and domain (the digital) through focused research, in order to produce practical guidance for start-up teams’ leaders and members in that location².

¹Regarding the filters (iv) and (v), we manually checked each firm’s websites to check if their offers included hardware devices and if they depended on a parent company. These filters eliminated x firms (x firms with hardware business propositions and x subsidiaries)

²We chose to study SaaS-based digital firms because their scalability echoes the efficient, pre-

INSERT TABLES 2 AND 3 HERE

Secondly, we use LinkedIn, a social networking service providing information on individuals' professional trajectories, to collect human capital - skills data of entrepreneurial teams of 498 digital firms, representing a total of x individuals. Virtual skill endorsement (skills endorsed and validated by peers on LinkedIn) is a socially constructed online reputation considered a piece of valuable information. Skill endorsement a way of self-presentation through which the job seekers brand themselves to the potential recruiters (?). Using LinkedIn has proven its relevance in recent entrepreneurship studies because it profiles detailed individual-level human capital data not available through more traditional sources. We selected carefully all founders that possess equity in the firm (??). Table TABLE4 list the descriptives statistics of all variables (means, std dev, min, max).

INSERT TABLE 4 HERE

dictable, and repeatable systems that provide investors with new opportunities offered by the non-linear revenues of digital technologies (the hardware being complicated to finance by investors) (?). Also, we chose the period 2010-2018 because it fits with private firms' mass adoption of cloud technologies in pre-existing markets. Indeed, these technologies recently revolutionized the software industry in various markets, e.g., supply chain, financial, accounting, human resources, or customer relationships, making it a topic of interest in various industries (?). Furthermore, we chose the Metropolis of Greater Paris (France) because it is a significant global city with labor and financial capital pools and proximate clients. The Metropolis of Greater Paris' financing and business landscape, especially its venture capital market, is one of Europe's largest, most structured, and most dynamic. From 2016 to 2020, SaaS-based firms accounted for 50% of the total amount raised in France, 75% of French fundraising rounds in Paris, and more than 85% of the amount and in values (BPI, 2020)

3.2 Dependent variable: fundraising

La performance des firmes digitales a été opérationnalisée de nombreuses façons parce qu'il n'y a pas de consensus dans la littérature sur la façon de mesurer leur performance. Par exemple, les chercheurs ont opérationnalisé la performance en termes de croissance (des ventes, d'emplois, de revenus), de rentabilité, de survie, d'innovation ou d'introduction en bourse (IPO) (?).

L'obtention d'un financement externe par un investisseur est la façon dont nous évaluons la performance des firmes digitales. Nous avons choisi la métrique *fundraising* car des recherches antérieures indiquent que recevoir un financement d'un investisseur est un prédicteur important de la survie et de la croissance future d'une firme (?). Notamment, l'insuffisance des ressources financières est fréquemment citée comme la principale cause de l'échec des nouvelles entreprises au début de leur cycle de vie (??). Nous avons donc deux populations bien distinctes dans notre échantillon : les firmes ayant reçu un financement de la part d'investisseurs externes, et celles n'en ayant pas reçu. Conformément aux études précédentes, nous utilisons le logarithme du premier tour de financement (*log fundraising*). Cette variable s'étend de x à une valeur maximale de x.

Enfin, nous avons ajouté la variable (*time to fundraising*) car du point de vue d'une start-up team, il est souhaitable d'obtenir un financement externe, idéalement peu de temps après la création de l'entreprise, afin d'embaucher plus de personnel et de faire croître l'entreprise. Nous utilisons Crunchbase pour identifier la date de création de l'entreprise et la date à laquelle le premier financement externe a été annoncé. Cette variable s'étend de x à une valeur maximale de x.

3.3 Independent variables

From a methodological point of view, we derived an outcome-based human capital indicator based on skills and expertise endorsement data which is considered a more direct measure of human capital and as one way of analyzing how skills affect firms' performance in a digital environment (?).

Le niveau de compétences est mesuré au travers d'une variable continue que nous nommons *level skills*, allant de x à x (x = faible niveau de compétences ; x = niveau maximum de compétences). Tous les individus sont placés sur ce continuum dans chacun des cluster de compétence que nous avons récupéré de LinkedIn. Nous attribuons à chaque start-ups teams de notre échantillon le score le plus élevé associé à l'un de ses fondateurs. Nous avons construit cette variable comme une variable continue car nous soutenons qu'un clustering dur (catégories) ne rendrait pas compte de la versatilité de l'effet proportionnel qu'il pourrait avoir sur la collecte de fonds (fuzzy clustering). Par conséquent, un score élevé correspond à un avantage supplémentaire pour les start-ups teams.

Heterogeneity variable based on the Blau's index score, where the variable is equal to $1 - \sum p_k^2$ where p is the proportion of unit members in k th category, ranging from zero to $k - 1/k$.

La variété des compétences est mesuré au travers d'une variable continue que nous nommons *variety skills*, allant de x à x (x = faible variété de compétences ; x = maximum variété compétences). Une start-ups team est considérée comme plus variée sur le plan fonctionnel si les individus sont également répartis dans toutes les différentes catégories fonctionnelles (Blau, 1977 / Hirshman), qui sont des groupes ayant des backgrounds communs. Following ?, we interpret a *variety skills* as the

composition of differences in skills among agents of a unit member, being here the start-up team. Based on LinkedIn individuals' skills and competencies data (from 1,100 unique agents, we gather 10,638 skills, including 5,449 unique skills). We assigned each founders in the dataset a score in ten functional areas (strategy, marketing, entrepreneurship, sales, software development, product, finance, management, human resources, and design). We used a bottom-up hierarchical clustering approach with Kruskal's minimum spanning tree algorithm (?) and considered the occurrences and co-occurrences of skills between founders. Therefore, the similarity between any pair of skills is naturally defined as the "intersection over union". Consequently, we set a founders' affinity to any skill cluster in the tree by measuring the skills they share. Instead of assigning a founder to the cluster with the highest affinity (hard clustering) that would not account for its versatility, we describe a founder with his set of affinities to the skills of interest (fuzzy clustering). Finally, we aggregated the founders's variety scores at the start-up team level. We can follow Mintzberg et Waters (1982), Pavett et Lou (1983) et Shein (1987) : il existe 3 rôles dans les entreprises : entrepreneurial (sales SaaS, Biz strat, designer, creation), manager (HR, finance, lawyer) et techniques (utilisation d'outils, procédures, techniques).

3.4 Control variables

We have included several control variables because the influence of other factors could skew our estimation.

Firm age (time since the founding date provided on Crunchbase) to incorporate a proxy for the new venture's stage of development (Zahra, Sapienza, and Davidsson, 2006)

First, we used the variable *size* to control for start-up team’s numerosity. Indeed a higher skill level and a greater variety of skills and conflicts among the members of an organization are implied by a larger population of individuals (?). Our sample has groups ranging in size from x to x.

Secondly, we used the variable *previous founder* whose minimum and maximum values are x and x, respectively, to control the number of firms previously founded by the individuals in our sample. Indeed, a more extensive entrepreneurial experience can increase investor confidence, send a signal of competence, and have an impact on the amount of raised funds. Prior successful foundational experience — mainly financial — increases the likelihood of financing and firm valuation (?).

Thirdly, using the variable *previous fundraising*, we controlled whether members of the start-up team had previously raised money from investors. Though the investors believe it, it is exceedingly difficult to determine whether serial entrepreneurs are better or worse than the other founders. Even serial entrepreneurs who have failed receive much better terms from investors even though their businesses perform less well when they receive funding (?).

With the variable *previous exit*, we partially controlled whether members of the start-up team had previously completed a successful exit. Indeed, ? suggests founders who start successful firms have much higher success rates in subsequent firms than founders of unsuccessful firms or first-time founders.

Also, with the *previous career* control variable, we could determine whether the start-up team members had any significant prior professional experience. Indeed, using human capital and signaling theory, ? investigated whether and how the human capital indicators of founders’ educational attainment, professional experience, and

personality traits affect early-stage venture capital (VC) investment. They concluded that founders with extensive professional experience attract higher initial investments than other founders.

Sixth, we used the *previous education* variable to determine whether the members of a start-up team attended a prestigious university. Indeed, X demonstrated that founders with degrees from first-plan institutions attracted significant early-stage investments. Additionally, teams founded by Ph.D. holders are more likely to receive funding and higher valuations, suggesting a signal effect. We Therefore have added the *previous Ph.D.* variable (?).

Jerome Note : The “Elite’s University” variable is constructed from a combination of the top 10 universities worldwide (ARWU 2022 ranking) and the best French business and engineering schools (Figaro Etudiant Ranking 2023). ARWU is not suitable for capturing the entrepreneurial elite graduated in France, due to the weight and attractiveness of French “Grandes Ecoles”, poorly represented in ARWU-type international rankings based on Clarivate bibliometric data . The student Figaro ranking integrates the quality of faculty recruitment, relations with industry, and the salary of graduate students.

Finally, we controlled for the birth date and industry in which the firm operates because there may be some confusion due to the financial circumstances in which digital firms operate. We have created six sectoral economic indicators (RH, BI), and one for each year between 2010 and 2018.

To add : ?

3.5 Econometric Specification

Dans cette étude, nous utilisons un Modèle linéaire généralisé utilisant une distribution binomiale négative. La régression binomiale négative sert à modéliser les variables de comptage, généralement pour les variables de résultat de comptage surdispersées (ici, le montant levé par la firme digitale) <https://stats.oarc.ucla.edu/r/dae/negative-binomial-regression/>

4 Results

4.1 Findings

4.2 Robustness tests

5 Discussion

Which start-up teams are funded by external investors and why are recurring themes in contemporary economic and entrepreneurial literature (?????????).

According to the literature, there are two types of diversity: surface-level differences (e.g., race, ethnic origin, age, etc.), and deep differences (e.g., education, skills, capacities, attitudes and personalities) (?).

This article investigates how start-up teams' compositions affect investors' assessments. By highlighting the significance of start-up teams' skill level and skill diversity in obtaining private funding, we try to understand why the results of previous studies on start-up teams' human capital could have been more consistent. Indeed, empiric results from entrepreneurship research have highlighted the founders' human capi-

tal as the primary driver of their ability to expand. However, these studies needed did not demonstrate how the skill level and skill diversity within a start-up team can influence a digital firm's success. By examining these two metrics together, this article attempts to center the investigation on the dynamics of early-stage start-up teams and determine how vital these characteristics are to the dynamics of interactions among team members and how they relate to the structure's proper operation. Given the significance of digital firms as a catalyst for economic development, these perspectives are significant for researchers, entrepreneurs, and policymakers.

The lack of research on multiple levels regarding human capital is the primary motivation behind this study. One issue is that the results of (?) show a strong bias toward the individual level, with little consideration given to the founding team or potential inter-individual synergies. Another reason is that the study context varies depending on the sample sizes and populations being looked at. For example, some analyze high-tech and textile industries, while others use samples of student entrepreneurs. After that, it becomes difficult to analyze this relationship without considering the specific circumstances and conditions that apply to a given event or situation, making the study's context — in this case, the digital environment — an essential factor. The insufficient precision of the independent variables used and constructed to represent the variables of human and social capital is a third reason (?). In addition to the challenge of incorporating multiple signals and their interactions into empirical studies, previous empirical studies frequently used raw measures of human capital, such as the level of years of education, entrepreneurial experiences, or professional experiences. Therefore, there is a clear need for more precise approaches that reflect a finer variation of human and social capital-related aspects. This article

focuses on the latter limit, i.e., we examined the combined effects of two variables and made suggestions regarding how they affect the ability of start-up teams to raise capital from investors. For this, we used a sample of 498 digital businesses with Paris headquarters that use the Software-as-a-Service (SaaS) business model, of which x raised money while x did not

Our findings demonstrate that, in line with the signal and human capital theory, a start-up team that is diverse in terms of skills is more likely to be financed by investors. Another significant moderator of the investment decision is the team size. On the other hand, consistent with our arguments, we discovered that investors favor start-up teams that have (i) either a high level of skills, (ii) either a high level of variety of skills, but not both at once. Because of this, start-up teams that contain highly skilled individuals in related fields, i.e., e. the diversity of their expertise is low, receive more financial resources. High levels of skills, however, hurt the amount and speed of funding start-up teams can secure from investors when their skills are diverse.

The article makes several contributions. First, our findings offer fresh avenues for reflection on the composition of start-up teams and the signal generated among investors. Indeed, past empirical studies have long focused on one of the two dimensions of start-up teams' skills. On the one hand, they either focus on their proficiency level, referring to the novice vs. expert, operationally measured by years of experience. On the other hand, they focus on the level of skills' variety, referring to the specialist vs. generalist and operationally measured by the Hirschman or Blau Index). However, when separated, a firm's success is not explained by either of these two dimensions. Furthermore, not only do some levels of skills only apply to some contexts, but certain

levels of variety of skills only apply to some contexts. Indeed, the digital context, in contrast to the industrial context, is governed by other social and technological specificities that require different signals. We suggest a methodology in which we assess these two aspects jointly in a digital context. Second, many empirical studies looking at how start-up teams' composition affects investors' evaluations focused on indicators such as education (?), entrepreneurial experience (?), industry experience (?), or leadership experience(?). In this article, we suggest a skill-based approach, i. e. we focus on "outcomes of human capital" (i. e., their knowledge, skills, and abilities) because they are thought to be more accurate and direct indicators than "investment in human capital" measures like education and years of experience (??). Third, this is a chance to focus on the most crucial systems for teams in that area. As previously mentioned, selecting teams from a wide swath of the landscape could introduce noise into a targeted investigation because the dynamics of composition for teams located in other regions may be quite different. By focusing our research on a small landscape area, we can create accurate theoretical models for that area and create helpful suggestions for team leaders and members of start-ups operating in that area

Recent empirical studies support the idea that multiple forms of diversity and organizational performance positively affect firm performance (?).

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6 Statements and Declarations

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8 Annexes

| Variable name | Description | Data source |
|--|---|----------------------|
| Dependent variable | | |
| 1. <i>Capital Raised (log)</i> | Natural logarithm of the amount of investment provided by external investors in the first round [€] | Crunchbase, BPI |
| Independent variables | | |
| 2. <i>Skills and expertise level</i> | Ordinate variable ranging from 1 to 10 (1= min; 10= max). Each start-up team is assigned the highest median score associated with any of its members | LinkedIn |
| 3. <i>Skills and expertise field diversity</i> | Blau index on the probability of finding a particular skill in a start-up team among the six group identified (i.e., Finance, Product, Development, Management, Marketing, Entrepreneurship) | LinkedIn |
| Control variables | | |
| Human Capital control variables | | |
| 4. <i>Previous Prestigious University</i> | Number of graduations from one of the best French business, engineering schools or from the 10 universities worldwide. Each start-up team is assigned the maximum score associated with any of its members | LinkedIn |
| 5. <i>Previous Founding Experience</i> | Number of unique ventures previously founded or co-founder. Each start-up team is assigned the maximum score associated with any of its members | LinkedIn |
| 6. <i>Previous Working Experience</i> | Maximum number of years of work experience of a start-up team member. Each startup team in our sample is assigned the highest score associated with any of its members | LinkedIn |
| 7. <i>Previous Ph.D Degree</i> | Number of Ph.D graduations. Each start-up team is assigned the maximum score associated with any of its members | LinkedIn |
| Firms control variables | | |
| 8. <i>Size</i> | Number of start-up team members | Crunchbase, LinkedIn |
| 9. <i>Firm age</i> | Number of years since firms' foundation | Crunchbase, BPI |
| 10. <i>Industry</i> | Ten industry dummies which take value 1 if the company is operating in i) Business Intelligence Analytics, ii) Customer Relationship Management, iii) Developers Software Infrastructure, iv) Education Human Resources, v) Finance Legal Insurance, vi) Healthcare, vii) Logistics Supply Chain, viii) Productivity Collaboration, ix) Real Estate Construction x) Retail Ecommerce Marketing, or xi) Security | Crunchbase, BPI |

Table 1: Variable definitions and sources

| Variables | Obs | Mean | SD | Min | Max |
|---|-----|--------|-------|-----|--------|
| Dependent variable | | | | | |
| <i>Fund received (log)</i> | 514 | 9.505 | 6.128 | 0 | 16.524 |
| Independent variables | | | | | |
| <i>Skills and expertise level</i> | 514 | 7.862 | 1.647 | 0 | 9.000 |
| <i>Skills and expertise field diversity</i> | 514 | 0.603 | 0.367 | 0 | 1 |
| Control variables | | | | | |
| Human capital control variables | | | | | |
| <i>Previous Prestigious University</i> | 514 | 1.185 | 1.342 | 0 | 8 |
| <i>Previous Founding Experience</i> | 514 | 3.518 | 2.180 | 0 | 13 |
| <i>Previous Working Experience</i> | 514 | 16.778 | 8.705 | 1 | 47 |
| <i>Previous PhD Degree</i> | 514 | 0.138 | 0.431 | 0 | 3 |
| Firms control variables | | | | | |
| <i>Size</i> | 514 | 2.374 | 0.907 | 1 | 8 |
| <i>Firm Age</i> | 514 | 5.228 | 1.963 | 2 | 9 |
| <i>Business Intelligence Analytics</i> | 514 | 0.070 | 0.255 | 0 | 1 |
| <i>Customer Relationship Management</i> | 514 | 0.054 | 0.227 | 0 | 1 |
| <i>Developers Software Infrastructure</i> | 514 | 0.080 | 0.271 | 0 | 1 |
| <i>Education Human Resources</i> | 514 | 0.111 | 0.314 | 0 | 1 |
| <i>Finance Legal Insurance</i> | 514 | 0.107 | 0.309 | 0 | 1 |
| <i>Healthcare</i> | 514 | 0.049 | 0.215 | 0 | 1 |
| <i>Logistics Supply Chain</i> | 514 | 0.060 | 0.238 | 0 | 1 |
| <i>Productivity Collaboration</i> | 514 | 0.140 | 0.347 | 0 | 1 |
| <i>Real Estate Construction</i> | 514 | 0.049 | 0.215 | 0 | 1 |
| <i>Retail Ecommerce Marketing</i> | 514 | 0.253 | 0.435 | 0 | 1 |
| <i>Security</i> | 514 | 0.027 | 0.163 | 0 | 1 |

Table 2: Descriptive statistics

Part A : Number of fundraising rounds per years

| Fundraising years | Amount in millions of euros | | | | | |
|-------------------|-----------------------------|-------|--------|-------|--------|-------|
| | Rounds | Mean | Median | Min | Max | SD |
| 2011 | 5 | 0.561 | 0.170 | 0.025 | 1.800 | 0.752 |
| 2012 | 7 | 0.977 | 0.700 | 0.100 | 2.500 | 0.879 |
| 2013 | 22 | 0.589 | 0.250 | 0.060 | 5.000 | 1.044 |
| 2014 | 33 | 0.841 | 0.390 | 0.055 | 8.000 | 1.502 |
| 2015 | 58 | 1.133 | 0.500 | 0.023 | 10.000 | 1.728 |
| 2016 | 62 | 1.091 | 0.400 | 0.050 | 12.000 | 2.143 |
| 2017 | 76 | 1.453 | 0.750 | 0.050 | 10.000 | 1.997 |
| 2018 | 45 | 1.756 | 1.000 | 0.020 | 15.000 | 2.529 |
| 2019 | 47 | 2.076 | 1.500 | 0.071 | 12.000 | 2.248 |
| 2020 | 12 | 2.584 | 1.250 | 0.500 | 14.500 | 3.930 |
| Total | 367 | 1.306 | 0.600 | 0.020 | 15.000 | 0.942 |

Part B : Fundraising per founding date

| Fundraising years | Amount in millions of euros | | | | | | |
|-------------------|-----------------------------|--------|-------|--------|-----|--------|-------|
| | Firms | Rounds | Mean | Median | Min | Max | SD |
| 2011 | 34 | 31 | 1.032 | 0.350 | 0 | 7.300 | 1.439 |
| 2012 | 43 | 32 | 1.024 | 0.400 | 0 | 12.000 | 1.975 |
| 2013 | 67 | 53 | 0.776 | 0.215 | 0 | 8.000 | 1.429 |
| 2014 | 75 | 55 | 1.335 | 0.200 | 0 | 15.000 | 2.700 |
| 2015 | 87 | 64 | 1.055 | 0.250 | 0 | 14.500 | 2.207 |
| 2016 | 96 | 72 | 0.975 | 0.475 | 0 | 12.000 | 1.770 |
| 2017 | 75 | 40 | 0.641 | 0.100 | 0 | 4.500 | 0.984 |
| 2018 | 37 | 20 | 0.999 | 0.500 | 0 | 8.800 | 1.660 |
| Total | 514 | 367 | 0.980 | 0.300 | 0 | 2.700 | 0.528 |

Table 3: Descriptive statistics of fundraising rounds

| Industry | Number of firms | % total |
|------------------------------------|-----------------|---------|
| Business Intelligence Analytics | 36 | 7 |
| Customer Relationship Management | 28 | 5.4 |
| Developers Software Infrastructure | 41 | 8 |
| Education Human Resources | 57 | 11.1 |
| Finance Legal Insurance | 55 | 13.3 |
| Healthcare | 25 | 6 |
| Logistics Supply Chain | 31 | 7.5 |
| Productivity Collaboration | 72 | 17.3 |
| Real Estate Construction | 25 | 6 |
| Retail Ecommerce Marketing | 130 | 31.3 |
| Security | 14 | 3.3 |
| Total | 514 | 100 |

Table 4: Distribution of sample : firms by industry classification

| | Model 1 | | | Model 2 | | | Model 3 | | |
|--|-----------|----------|---------|-----------|----------|---------|-----------|----------|---------|
| Observations = 514 | Prob. > F | 0 | | Prob. > F | 0 | | Prob. > F | 0 | |
| | R-squared | 0.17 | | R-squared | 0.18 | | R-squared | 0.19 | |
| Variables | Coef. | Std.Err. | p value | Coef. | Std.Err. | p value | Coef. | Std.Err. | p value |
| Skills and expertise level (SL) | | | | 0.287 | 0.120 | 0.017 | 0.597 | 0.160 | 0.000 |
| Skills and expertise field diversity (SFD) | | | | | | | 5.494 | 1.866 | 0.003 |
| Interaction SL * SFD | | | | | | | -1.167 | 0.446 | 0.009 |
| Previous Prestigious University | 1.513 | 0.341 | 0.000 | 1.429 | 0.341 | 0.000 | 1.406 | 0.339 | 0.000 |
| Previous Founding Experience | 1.028 | 0.266 | 0.000 | 0.923 | 0.268 | 0.001 | 0.892 | 0.267 | 0.001 |
| Previous Working Experience | -0.004 | 0.031 | 0.911 | -0.018 | 0.031 | 0.573 | -0.017 | 0.031 | 0.588 |
| Previous PhD Degree | 0.190 | 0.617 | 0.759 | -0.032 | 0.617 | 0.959 | -0.140 | 0.615 | 0.819 |
| Firm Age | 0.609 | 0.139 | 0.000 | 0.553 | 0.140 | 0.000 | 0.584 | 0.140 | 0.000 |
| Business Intelligence Analytics | -0.173 | 0.935 | 0.853 | -0.197 | 0.931 | 0.832 | -0.372 | 0.926 | 0.688 |
| Customer Relationship Management | -1.120 | 1.047 | 0.285 | -1.387 | 1.048 | 0.186 | -1.350 | 1.042 | 0.196 |
| Developers Software Infrastructure | 1.345 | 0.878 | 0.126 | 1.407 | 0.874 | 0.108 | 1.131 | 0.876 | 0.197 |
| Education Human Resources | 2.109 | 0.751 | 0.005 | 1.721 | 0.765 | 0.025 | 1.664 | 0.761 | 0.029 |
| Finance Legal Insurance | 1.095 | 0.775 | 0.158 | 1.029 | 0.772 | 0.183 | 0.864 | 0.769 | 0.262 |
| Healthcare | 1.610 | 1.131 | 0.155 | 1.579 | 1.126 | 0.161 | 0.897 | 1.142 | 0.432 |
| Logistics Supply Chain | 0.881 | 0.985 | 0.372 | 0.583 | 0.988 | 0.555 | 0.358 | 0.986 | 0.717 |
| Productivity Collaboration | -1.679 | 0.685 | 0.015 | 1.790 | 0.683 | 0.009 | -1.998 | 0.682 | 0.004 |
| Real Estate Construction | 1.241 | 1.094 | 0.257 | 1.153 | 1.090 | 0.290 | 0.636 | 1.097 | 0.562 |
| Retail Ecommerce Marketing | -0.444 | 0.551 | 0.421 | -0.622 | 0.554 | 0.262 | -0.697 | 0.552 | 0.208 |
| Security | -1.034 | 1.449 | 0.476 | -0.502 | 1.459 | 0.731 | -0.536 | 1.450 | 0.712 |
| Intercept | 3.831 | 0.842 | 0.000 | 2.976 | 0.910 | 0.001 | 0.597 | 1.237 | 0.630 |

Table 5: OLS regression