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The effect of human capital and common ground on human capital investments

Master Thesis in Management Engineering – Ingegneria Gestionale

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Abstract

Existing literature has studied the relevance of human capital and common ground for start-ups' survival and growth. However, previous research has rarely discussed these two concepts together in the context of newly born companies. Therefore, the research question we address is how the prior knowledge of entrepreneurs in a specific knowledge domain and the common ground among team members influence entrepreneurs' human capital investments in that domain. Indeed, the individual's decision to invest is thought to be impacted by both individual and start-up team's characteristics. To answer this question, we joined the InnoVentureLab research team, which provided a training program to 151 Italian ventures in the pre-scaling phase. This allowed us to collect primary data about the entrepreneurs. Our econometric analysis reveals that there is a negative linear relationship between entrepreneurs' prior knowledge and the probability that they invest in human capital by attending the lectures. Indeed, the decision to invest is driven by the returns generated at the start-up and individual's levels, which decline at an increasing rate as the prior knowledge of the investment's subject increases. On the one hand, when entrepreneur's teammates lack competences in the domain, the negative relationship gets steeper, because the investment partially fills the knowledge gap of peers, thus increasing returns; on the other hand, when teammates have specific competencies, the relationship flattens and loses statistical significance. Furthermore, unexpectedly, common ground among team members has no statistically significant effect on the principal relationship. These unexpected results could be related to low sample heterogeneity as well as the approach used to estimate common ground.

Keywords: human capital investments, common ground, specific knowledge, start-ups, pre-scaling.

Abstract in italiano

La letteratura esistente ha studiato la rilevanza di capitale umano e common ground per la sopravvivenza e la crescita delle start-up. Tuttavia, la ricerca ha raramente discusso questi due concetti insieme nel contesto imprenditoriale. Pertanto, la domanda di ricerca che formuliamo è come la conoscenza pregressa degli imprenditori in uno specifico dominio e il common ground tra i membri del team influenzino gli investimenti in capitale umano degli imprenditori in quel medesimo dominio. Infatti, si ritiene che la decisione del singolo di investire sia influenzata sia da caratteristiche individuali sia del team imprenditoriale. Per rispondere a questa domanda, ci siamo uniti al team di ricerca InnoVentureLab, che ha offerto un programma di formazione a 151 start-up italiane in fase di pre-scaling. Questo ci ha permesso di raccogliere dati primari sugli imprenditori. Dalle nostre analisi econometriche emerge l'esistenza di una relazione lineare negativa tra le conoscenze pregresse degli imprenditori e la probabilità che essi investano in capitale umano frequentando le lezioni. Questo accade poiché la decisione di investire è guidata dai ritorni generati a livello individuale e di start-up, che diminuiscono con ritmo crescente all'aumentare della conoscenza pregressa nell'ambito dell'investimento. Inoltre, quando i membri del team imprenditoriale non hanno competenze nel settore, la relazione negativa diventa più ripida, poiché l'investimento colma parzialmente il divario di conoscenza dei membri del team, aumentando così i ritorni dell'investimento; invece, quando i membri del team possiedono competenze specifiche, la relazione si appiattisce e perde significatività statistica. Inaspettatamente, il common ground tra i membri del team non ha effetti statisticamente significativi sull'associazione principale. Questi risultati imprevisti potrebbero essere attribuiti alla bassa eterogeneità del campione e all'approccio utilizzato per stimare il common ground.

Parole chiave: investimenti in capitale umano, common ground, conoscenza specifica, start-ups, pre-scaling.

Contents

List of Figures

List of Tables

Executive summary

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1. Introduction

Investments in human capital are an important source of value for companies at all stages of their development. Furthermore, the level of coordination among team members is another crucial factor to make a business thrive. The level of coordination can be affected by several factors, and one of them is the common ground, which can be seen as the set of beliefs and shared experiences that enable the transfer of knowledge and coordination between individuals. Usually, scholars mainly focused their works on human capital and common ground by addressing them as separate concepts. Besides that, they have never studied their interaction focusing on one of the most delicate phases of the life cycle of a venture, namely the pre-scaling stage. Therefore, the present Master Thesis investigates the following research question:

How do entrepreneurs' human capital and common ground affect the human capital investments made within a start-up?

To do so, the research is organized as follows: in section 2, we summarized the key academic works that we analysed to conduct our research; in section 3, we will present our theoretical framework by discussing our hypothesis; chapter 4 deepens the method that we used to conduct our research, while chapter 5 presents our empirical analysis; lastly, chapter 6 offers our conclusive reasonings about the key findings of our work.

2. Literature review

2.1. Human capital

Human capital is defined as the set of knowledge and skills that individuals possess that are acquired through education and training. According to Marvel et al. (2016) human capital factors influence the transition from one stage of the entrepreneurial process to the next. Indeed, human capital components are key in each stage of the business development: they improve the odds of survival and growth of a start-up from the identification and exploitation of entrepreneurial possibilities until the eventual stage of business scaling. However, the notion of human capital encompasses a wide range of competences and skills that can be considered relevant depending on the business. Indeed, human capital can be differentiated between general and specific human capital. General human capital refers to basic knowledge acquired by individuals via formal education and professional experience, while specific human capital regards all the skills that can be directly applied in a newly formed start-up.

2.2 Common ground

Common ground can be defined as a type of self-awareness in which at least there is another individual who possesses a similar level of self-awareness (Clark, 1996). This concept can be seen whenever an interaction between two individuals occurs. When we interact with someone we rely on a set of knowledge, beliefs, and suppositions that we assume to share with the other person while having the conversation. This set of shared knowledge may come from similar experiences that both individuals have lived and now are taken from granted by both interlocutors. In general, this set of shared experiences enhances a deeper level of understanding and agreement between people that can contribute to a higher level of coordination. In fact, is not uncommon to see EFTs formed by similar members that share some prior experience or they are bound by a family tie.

2.3. Scaling

The life cycle of a company from an entrepreneurial perspective can be seen through the four phases of "start-up", "transition", "scaling" and "exit" (Picken, 2017). Unfortunately, literature does not provide a unique definition of the concept of scaling and pre-scaling, as scholars mainly investigated the so called "start-up" phase. The most involved metrics to define the concept of scaling regard the amount of funds, the age of the venture, the sales and employment growth and the valuation. The boundaries become even more fuzzy when addressing the concept of pre-scale-ups. In this case, literature does not provide a definition of the concept but define it just as the phase before the scaling (Picken, 2017) without providing any metrics.

3. Theoretical Framework

In order for an entrepreneur to pursue an investment in human capital, the expected returns must be greater than the entrepreneur's investment costs. Therefore, we can assume that the choice of investing in human capital is governed by the returns that the investment generates at start-up and individual's level. The returns of a human capital investment made in a specific knowledge domain decrease at an increasing rate, since as people's prior knowledge of the investment's topic rises, they receive less benefit from it. Therefore, we can conclude that the level of investment in human capital strictly depends on the return trend. Indeed, as the specific knowledge of the entrepreneur in that domain increases, he will benefit less from the investment and therefore will be less keen on facing it. Thus, we derive the following hypothesis:

Hypothesis 1 (H1): *There is a negative linear relationship between the human capital investments of an entrepreneur in a specific knowledge domain and the knowledge the entrepreneur already possesses in the domain.*

We will now focus on the same relationship addressed in hypothesis 1 while taking into account the effect of team members' competencies. Indeed, we will examine how the competencies of peers affect the expected positive returns on human capital investments made by entrepreneurs. We anticipate that, by considering this new component, the original relationship will be either strengthened or weakened. We assume that when teammates already have some competencies in the domain in which the entrepreneur is making the investment, the expected positive effects on the venture are somehow lower compared to those predicted in hypothesis 1, since there is not a complete knowledge gap to be filled. However, acquiring some competences in the domain would allow the entrepreneur to better interact with his teammates, act more quickly, and create synergies for the venture (Zheng at al., 2016). Instead, when teammates have no competencies in the domain, the expected positive effects on the venture are the highest since there is a significant knowledge gap to be addressed, and the investment in human capital will at least partially fill it. Thus, we derive the following hypotheses:

Hypothesis 2a (H2a): *The negative linear relationship between the human capital investments of an entrepreneur in a specific knowledge domain and the knowledge the entrepreneur already possesses in the domain flattens when the entrepreneur's teammates have already competences in the domain.*

Hypothesis 2b (H2b): *The negative linear relationship between the human capital investments of an entrepreneur in a specific knowledge domain and the knowledge the entrepreneur already possesses in the domain steepens when the entrepreneur's teammates do not have competences in the domain.*

Furthermore, we argue that team members' common ground can play a role in altering the relationship defined in hypothesis 1. In general, entrepreneurs with higher specific knowledge are likely to be familiar with some of the training program's contents; consequently, they will suffer a smaller opportunity cost thanks to their greater absorptive capacity, namely the ability to assimilate and utilize outside knowledge (Cohen and Levinthal, 1990). Indeed, absorptive capacity increases with higher prior related knowledge. On the other hand, people with low specific education will face higher opportunity costs, since they may require longer to comprehend and assimilate all the concepts learned during training. Considering that start-up members want to reduce the opportunity costs associated with human capital investments, the most cost-effective option is for experienced team members to attend the course and then share what they learn with their colleagues. More experienced members can obtain new information at a lower cost, and then exploit the common ground to successfully transfer it to less knowledgeable colleagues. As a result, we anticipate that the likelihood of attending the training will increase as the entrepreneur's specific skills grows when there is common ground among team members. When the returns from human capital investments are larger at start-up level (i.e., when the start-up has a knowledge gap), the presence of common ground will have a greater beneficial influence on the venture, whereas the effect will be minimal when the investments' gains for the venture are small. So, we formulate the following two hypotheses:

Hypothesis 3a (H3a): *The linear relationship between the human capital investments of an entrepreneur in a specific knowledge domain and the knowledge the entrepreneur already possesses in this domain becomes positive when the entrepreneur's teammates already have competences in the domain and share common ground.*

Hypothesis 3b (H3b): *The linear relationship between the human capital investments of an entrepreneur in a specific knowledge domain and the knowledge the entrepreneur already possesses in this domain becomes even more positive when the entrepreneur's team mates do not have competences in the domain and share common ground.*

4. Method

4.1. Research Design

In order to test our hypotheses, we joined InnoVentureLab, a free online pre-acceleration program that aims to transfer methodologies and resources to assist start-ups in the development of their business model. We selected for the course 151 start-ups in pre-scaling phase that joined the 4 lectures and seminars offered by InnoVentureLab.

Specifically, start-ups were selected by checking their legal status and growth, whether they had already developed a prototype or an MVP and whether they were innovative start-ups searching for funds for the scaling phase.

4.2. The model's variables

Throughout the training programme, we maintained track of entrepreneurs' attendance at each of the four lectures. At the completion of the program, we used this data to create our dependent variable, **D_Attendance**, which assumes value 1 if the entrepreneur attended the lecture; it is a proxy for the entrepreneur' investment in human capital. For each participant, there are four attendance records in the dataset. Instead, to shape entrepreneurs' specific knowledge, we built the explanatory variable **Spec_Education**, which indicates how many years the entrepreneur spent studying economics, finance, management, and entrepreneurship at the university. Furthermore, we included a set of controls to improve the internal validity of our research. The controls address entrepreneur's characteristics, start-up's characteristics and general characteristics of the lectures. Moreover, to test H2 we built the moderator **D_Other_SE**, which is a dummy that assesses whether teammates have specific competencies in the domain of the investment; to test H3, instead, we built the moderator **D_Same_Firm**, which indicates whether the entrepreneur has previously shared professional experiences with his teammates.

5. Empirical Analysis

5.1 Hypothesis 1

We investigate the relationship between human capital investments and specific knowledge via econometric estimates of a model that links entrepreneur's attendance at the training program to a variable describing his specific human capital and a set of control variables. The basic statistical model that describes the probability of attendance is as follows:

$$Prob(D\_Attendance) = b_0 + b_1 Spec\_Education + \gamma Controls + \varepsilon$$

Empirical results are reported in Table 1:

D_Attendance	Coef.	St. Err.	Sig
Spec_Education	-.042	.017	**
D_Others_SE	-.367	.127	***
D_Same_Firm	.213	.04	***
Gen_Education	-.075	.017	***
D_Female	-.147	.104	
D_Other_Activity	-.184	.043	***
Ln_Team_Size	-.707	.037	***
D_Others_Lecture	-.553	.293	*
Module : base 1	0	.	
2	-.442	.063	***
3	-.568	.062	***
4	-.51	.071	***
D_Treatment	-.148	.069	**
Constant	1.595	.16	***

*** $p<.01$, ** $p<.05$, * $p<.1$

Table 1: Statistical model of H1

The coefficient of the independent variable is negative and significant *(β=-0.042, P=.013)*, revealing the presence of a small but significant negative linear relationship between the entrepreneurs' prior education in economics and management disciplines and his investment in human capital in the same domain. As a result, **hypothesis 1 is validated**: the probability that an individual will attend a lecture diminishes as his level of expertise in the subject area in which he is acquiring new knowledge increases. Indeed, the more entrepreneurs are knowledgeable about the subject, the less advantageous it is for them to attend the course due to their prior competencies. See Figure 1 for a graphical representation.

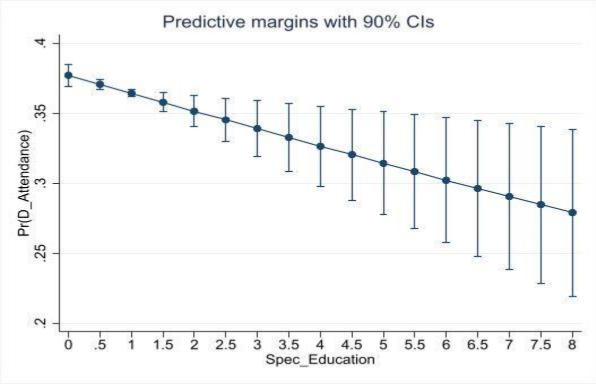

Figure 1: Predictive probability of attendance at different levels of specific education

5.2. Hypothesis 2

To test H2, we will now introduce a second level of analysis, namely the start-up perspective. We focus on the same relationship that was addressed in the previous hypothesis while adding the moderation effects of team members' competencies. Thus, the statistical model used to test H2 is the following:

$$Prob(D\_Attendance) = b_0 + b_1 Spec\_Education + b_2 D\_Others\_SE + b_3(D\_Others\_SE * Spec\_Education) + \gamma Controls + \varepsilon$$

The analysis reveals that the interaction term is significant *(P=.047)*, indicating that the competencies of the other members of the entrepreneurial team have a significant moderation effect on the outcome. However, the significant interaction term tells us that the slopes of the regression lines differ from each other but not whether each slope differs from zero. When at least one of the entrepreneur's teammates has economic, managerial or entrepreneurial knowledge (i.e., D_Others_SE=1), the linear decreasing relationship between an individual's likelihood of participating in the lecture and his specific knowledge flattens. However, the coefficient of Spec_Education is not statistically significant *(P=0.238)*; as a result, we cannot tell that the slope of the line representing the relation between attendance and specific education when teammates have competencies in the domain significantly differs from zero. Thus, **hypothesis 2a is not validated.** We believe that the coefficient's insignificance may be related to sample characteristics. Indeed, specific education values are mainly small (mean is 1.11), implying that most of the entrepreneurs did not study management and economics at university. As a result, most teams will almost certainly have knowledge gaps. Hence, due to the small number of observations, evidence of a significant effect cannot be provided in the case of knowledgeable teammates. Instead, when no one of the entrepreneur's teammates has specific knowledge (i.e., D_Others_SE=0), the linear decreasing relationship between an individual's specific knowledge and his likelihood of attending the course becomes stronger. Indeed, the slope of the regression line is **-0.087** and it is statistically different from zero *(P=0.020)*. When the moderation effect is included, the regression line gets steeper and therefore originates at higher probabilities of attendance. Thus, **hypothesis 2b is supported**: when teammates lack management, economics, or entrepreneurial knowledge, there is a higher likelihood that the entrepreneur will invest in human capital when he has low levels of prior knowledge. This happens because investing in the domain will provide the highest expected returns by filling the knowledge gap of peers.

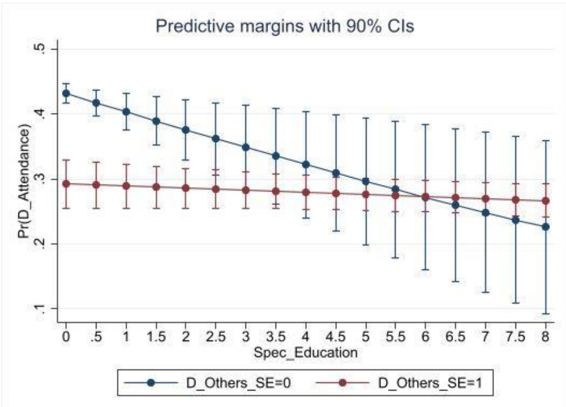

Figure 2: Predictive probability of attendance with respect to team members' competencies at various levels of specific education

5.3. Hypothesis 3

To test hypothesis 3, we add another moderator variable to the previously established relationship, resulting in a three-way interaction between one continuous variable and two categorical variables. The statistical model used to test H3 is as follows:

$$Prob(D\_Attendance) = b_0 + b_1 Spec\_Education + b_2 D\_Team\_SE + b_3 D\_Same\_Firm + b_4 (D\_Other\_SE * D\_Same\_Firm * Spec\_Education) + \gamma Controls + \varepsilon$$

We plotted the relationship in Figure 3 and 4.

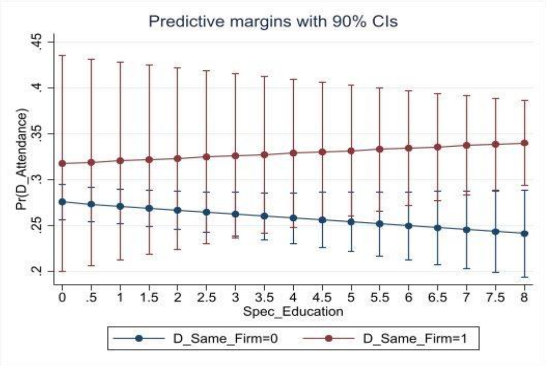

Figure 3: D_Others_SE=1

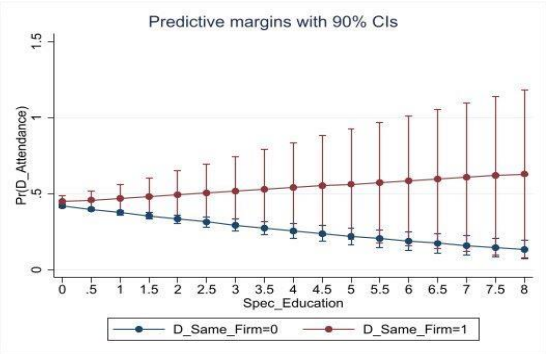

Figure 4: D_Others_SE=0

Figure 3 and 4: Predictive probability of attendance with regard to team members' competencies and common ground at various levels of specific education

The three-way-interaction term has significant coefficient, meaning that there is a statistically significant interaction between the three variables considered. When at least one of the entrepreneur's teammates has specific knowledge in the domain (i.e., D_Others_SE=1), the coefficients of the slope of the regression line is -0.016 (*P=0.252*) when there is no common ground among teammates, and 0.009 *(P=0.646)* when there is common ground. Since the coefficients of the independent variable are not significant (meaning that they are not statistically different from each other and not even statistically different from zero), **we have to reject hypothesis 3a.** Instead, when teammates have no specific competencies and there is no common ground among teammates, the coefficient of Spec_Education is negative and significant (*β=-0.137, P<.01*). Thus, the relationship presented in hypothesis 1 is strengthened: indeed, less knowledgeable entrepreneurs in a team with a knowledge gap may choose to invest more in training, knowing that it may be the only option to effectively learn new knowledge. When teammates have no specific competencies and there is common ground among teammates, the slope of the regression line is positive, equal to 0.069 *(P=0.594)*. However, due to the insignificance of the coefficient, **hypothesis 3b is not verified**. As a result, we have to conclude that common ground has no statistically significant effect on the relationship. A reason why results may have defied expectations is the nature of the common ground data, which does not indicate whether team members who worked in the same firm actually interacted with each other there. We then ran a robustness check, in which we tested our hypotheses with a continuous dependent variable. The robustness check results partially contradicted the findings of the main analysis, as hypothesis 2a was rejected and interaction terms were never found to be statistically significant. However, we believe that the non-significance of the results obtained in this test may be due to the fact that the attendance data we collected are subject to potential bias (e.g., they may have been altered by connection drops).

6. Conclusions

6.1. Discussion

This work investigates the entrepreneur's decision to invest in human capital as driven by both individual and start-up team's characteristics. Our econometric analyses showed the presence of a small but significant negative linear relation between the level of specific knowledge of entrepreneurs and the probability to invest in human capital (i.e., the likelihood of attending a lecture), which confirmed our first hypothesis. Furthermore, we identified two moderators that could affect this relation. The empirical analysis showed that when the entrepreneurial team has a substantial knowledge gap in the domain, the original linear decreasing relationship steepens, implying that there is a higher likelihood that the entrepreneur will invest in human capital when he has low levels of prior knowledge. Thus, hypothesis 2b was verified. Hypothesis 2a, instead, was not supported due to statistical insignificance. In addition, both hypotheses 3a and 3b were not validated because of statistical insignificance: from our analyses it resulted that common ground among teammates does not have a statistically significant impact on the original relationship.

6.2. Theoretical and practical implications

In this dissertation, we bring substantial theoretical contributions to the current literature. To begin, our study enriches the body of human capital entrepreneurship literature by investigating an unusual set of start-ups, specifically those in the pre-scaling phase. This research also adds to the existing studies on the dynamics of human capital investments made by start-ups by focusing on both personal and entrepreneurial team characteristics. Indeed, we have investigated how entrepreneurs' previous human capital in a domain influences further investments in that domain and how teammates' prior human capital and interpersonal characteristics moderate this relationship. Overall, we provide an answer to the fundamental question of what factors influence start-ups' decisions to acquire additional human capital in a knowledge area. From a managerial standpoint, we attempt to identify the level of human capital investment that start-up members believe is appropriate, as well as who is in charge of making the investment.

6.3. Limitations and future research

We acknowledge that our study has some limitations, which may realistically open the path to future research. To begin, there are some constraints on the generalizability of our results, which are linked to the way the selection process was conducted; additional studies on the definition of pre-scaling ventures and the use of a more heterogeneous sample may benefit the generalizability of future research's results. Another limitation concerns the fact that the results of the robustness check partially contradict the findings obtained in the main analysis. In this regard, further studies may solve these issues using a more robust proxy of human capital investments (e.g., training composed by more lectures or longer lectures). This would allow us to discern whether our results are contaminated by some bias. Third, common ground variables do not take into account when the shared experience dates back. Further research could deepen the relationship investigated in this thesis by employing different proxies of specific knowledge (e.g., previous experiences in the entrepreneurial field or working experiences in financial/ administrative roles). Moreover, it may be worthwhile to investigate whether our findings apply equally to ventures in different stages of the life cycle, such as early-stage start-ups or established businesses. Doubtlessly, the unexpected results obtained testing hypothesis 3 require additional explanation: it may be interesting for other researchers to discover whether or not common ground has a moderation effect on the relationship. Finally, future research may benefit from examinations of firm-level human capital conceptualizations.

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1 Introduction

The term "start-up" is now used in a wide range of contexts and circumstances. However, no one denies that starting a new business is a risky and challenging process (Chrisman et al., 2005). This difficulty stems from the status of uncertainty under which the company operates. Indeed, start-ups are defined as ventures that commercialize products or services in markets under great uncertainty (Ries, 2011). The firms that can manage the level of uncertainty can reach the scalability and repeatability of the business model, which are two essential characteristics of a start-up's success (Blank, 2020). As Picken (2017) pointed out, start-ups go through a four-stage life cycle and face several challenges as they expand and build their businesses. In the early stages, a company must validate the business concept by determining whether the idea has market traction. Indeed, one of the reasons for start-ups' failure is the lack of a defined process for identifying the appropriate customer segment, defining the market to compete in, and validating the hypothesis on which the business is based (Trimi and Berbegal-Mirabent, 2012). The transition phase begins once the enterprise has found traction in the market, and it represents an important step towards the rapid growth of the business (Picken, 2017). To reach the scaling stage, the entrepreneur must build new capabilities and add several resources that raise the complexity of coordination and execution throughout the whole founding team (Hambrick and Crozier, 1985). Between the transition and the scaling phases, the knowledge of the founding team and the capability of coordination are essential factors to decree the venture's success or failure.

Indeed, the step towards the scaling phase represents one of the major stages of the growth of a company. This achievement seems reachable only if team members have the knowledge needed to make the business grow. As regards team members, we formally rely on the definition of entrepreneurial founder team (EFT): a group of owners that hold a key role in the strategic decision making of the venture at the time of founding (Ucbasaran et al., 2003). Instead, by knowledge we define all the competencies and skills that an entrepreneur possesses to nurture the success of the venture. These developed abilities are as worthy as other resources used by the company to deliver value to the customers (Lucas, 1988). Indeed, each experience and education path can represent an investment that yields some returns in terms of future success of a business. For instance, education is one of the crucial factors that contribute to the acquisition of knowledge and competencies for the venture. This set of competencies and skills are encompassed in the notion of human capital: "the knowledge and skills that people acquire through education and training being a form of capital, and that this capital is a product of deliberate investment that yields returns" (Schultz, 1961). The human capital required for the growth of a firm in the context of start-ups addresses many knowledge areas. There is no requirement for all competencies to be present in a single individual, but they should be distributed across all members of an entrepreneurial team. While Schultz's definition refers to human capital in general, start-ups are interested in a closer set of abilities and skills. For example, if a member of an entrepreneurial team has a PhD in biology and his start-up works in the aerospace industry, his high degree of education seems to be useless. Thus, we have to differentiate between general human capital and specific human capital (Becker, 1964). The general one considers all types of education and professional experience of individuals, while the specific one, when applied to the entrepreneurial setting, refers to all skills that are useful and directly applicable in the new venture (Colombo et al., 2004). Indeed, there are technical competencies that are required for some industries, while others seem to be transversal to all sectors. These are the managerial and economic abilities and competencies required for a start-up: how to collect and manage funds, how to exploit resources, and how to manage people. This research, in particular, shapes specific knowledge as the years of university education in management and economical fields. Thus, the specific knowledge is considered as a proxy of the skills and competencies that are required to get thorough the transition phase and reach the scaling phase of the life cycle of a start-up.

Another issue that can hinder a start-up from reaching the scaling stage is a lack of communication among team members. In order to work together and make strategic decisions, the members of an EFT must succeed in communicating and coordinating the various activities. Indeed, the fit among them is a crucial aspect and intuitively is reasonable to assume that peers with similar attitudes get along well. Similar individuals in terms of ascriptive characteristics (e.g., gender, age and ethnicity), achieved characteristics (e.g., work experience and education) and internal psychological states such as values and beliefs tend to communicate better (Ruef et al., 2003; Forbes et al., 2006). Indeed, these shared characteristics enhance a higher level of social cohesion among team members that is essential to promote the transfer of knowledge (Reagans and McEvily, 2003). Nonetheless, Eisenhardt and Schoonhoven (1990) found a relationship between heterogeneity in industry experiences and higher growth rate of start-ups. The interaction between individuals that can happen in different contexts such as the workplace or the university gives the possibility to observe how peers think and what skills they have. Beside the concept of observation, the continuous interaction helps to develop mutual trust among individuals and gives the chance to spot possible team members for future businesses (Ruef et al., 2003). However, an EFT composed by similar members could lead to knowledge gaps and difficulties when dealing with problematic issues. In general, prior ties can be built in every circumstance and context with individuals that live our same events. When an interaction occurs between two individuals, each of them takes from granted that the interlocutor possesses a certain level of knowledge and lived some experiences. In this way, each of them tailors the speech accordingly. This approach of considering the knowledge of the other person while having a discussion happens more broadly any time that we interact with someone, and it can be intended as a self-awareness of the knowledge shared. The formal definition of this concept is common ground and was theorized by Harbert H. Clark (1996) as a type of self-awareness, self-knowledge, self-belief, and self-assumption in which there is at least one other person who possesses a similar level of self-awareness. So, common ground helps to build a trustworthy relation between us and our acquaintances by relying on a certain set of beliefs and shared experiences that we take from granted. This factor enhances the level of coordination among team members (Klein et al., 2005) by reducing the possible ambiguities that can arise from the misunderstanding of strangers.

The two concepts of human capital and common ground can have a significant impact respectively on the abilities and coordination of an EFT. Usually, start-ups suffer from a liability of newness due to missing capabilities and resources that can prevent the growth and possible scaling of the business (Cafferata et al., 2009). Indeed, a newly born venture can possess enough common ground to enable a fruitful communication while lacking on the specific human capital required to run the business. For this reason, start-ups typically experience a professionalization period during which new skills are easily learned to aid in growth and scalability (Boeker and Karichalil, 2002). These missing competencies can be acquired through investments in human capital. Moreover, when team members participate in training sessions as part of an investment in their human capital, new common ground can be developed and that will facilitate communication in the future. The aim of this dissertation is specifically to expand our knowledge regarding the relationship between entrepreneurs' human capital investments and the human capital they possess, considering also the effect of the team members competencies and common ground.

As may be observed intuitively, this thesis tries to keep a double point of view, focusing on both the individual and the entrepreneurial founding's team level. Indeed, we describe the entrepreneur's decision to invest in human capital as driven by both personal and start-up team's characteristics. Moreover, our unit of research are start-ups in the pre-scaling stage, since we acknowledge that human capital and common ground can have a relevant role on the future possible scaling of the business (Hambrick and Crozier, 1985; Picken 2017).

This work investigates the forehead mentioned topic through the formulation and assessment of three hypotheses. The first one analyses the relation between the specific knowledge of the entrepreneur and his level of human capital investment. The second hypothesis considers the specific competencies of entrepreneur's team members and their moderation effect on the previous relation; in particular, it investigates the entrepreneur's human capital investment in a specific knowledge domain when his teammates possess or do not possess specific competencies. Lastly, the third hypothesis deepens the relation expressed in the first hypothesis considering the moderation effect of the common ground shared among team members.

In order to test the hypotheses, we joined the InnoVentureLab research team and helped them organize a randomized control trial (RCT), which involved 151 Italian ventures in pre-scaling phase. The pre-acceleration program aimed to transfer methodologies regarding the management of financial resources. The training was structured into four online sessions and the participants were randomly assigned to either a treatment or a control group. The teachers of the programme adopted two different approaches to transfer the notions of financial management: with the treatment group, the instructors adopted a scientific approach by using frames to identify problems, formulate falsifiable hypotheses and test them meticulously. Instead, the control group was taught with standard training content relying more on heuristics and reflections on real cases, in order to encourage the entrepreneurs to make their own reasonings without being guided.

We participated to the online sessions as research assistants, and we gathered data about the attendance of each entrepreneur at the training program while monitoring their activities month by month. In this way we had the chance to analyse their level of participation to the course and their choices regarding teammates involvement. Once the attendance of the entrepreneurs had been collected, we focused on measuring their level of specific knowledge, shaping it through the years of specific education. Therefore, we gathered all the information regarding the education level of entrepreneurs in economical and management areas. This data was essential to test the first hypothesis, which investigated the relation between attendance and specific knowledge. Then, to test the second hypothesis, we also considered the competencies of team members in economics and management areas. Lastly, to test the third hypothesis, we collected information regarding the presence of common ground among team members, namely if they had previously worked together in the same company.

Our empirical results are fully in line with the first hypothesis. Indeed, we find a negative linear relation between the probability of investing in human capital (i.e., the attendance to the course) and the level of specific knowledge of entrepreneurs. The second hypothesis, instead, is partially verified: when entrepreneur's teammates lack competences in the domain, the negative relationship gets steeper; when teammates have specific competencies, instead, the relationship flattens and loses statistical significance. Lastly, the third hypothesis is not validated: common ground among team members has no statistically significant influence on the relationship. The results' insignificance, in our opinion, can be attributable to low sample heterogeneity as well as the approach used to measure common ground.

This study brings major theoretical contributions to the existing literature. To begin, our research adds to the body of human capital entrepreneurship literature by focusing on a unique set of start-ups, notably those in the pre-scaling stage, which are rarely addressed in the literature. This study also enriches existing research on the dynamics of human capital investments made by start-ups by focusing on both personal and entrepreneurial team characteristics, which have not yet been empirically examined. Furthermore, we investigate the interaction between the various moderators of the association between entrepreneurs' human capital and their likelihood of investing in human capital. Overall, we address the fundamental question of what factors impact start-ups' decisions to invest in additional human capital in a certain knowledge field. From a managerial standpoint, we attempt to identify the level of human capital investment that start-up members believe is appropriate, as well as who is in charge of making the investment.

The remainder of this thesis is organized as follows. The second chapter deeply analyses the literature of the two main topics that are behind our hypotheses, namely human capital and common ground, and tries to define in a clear and quantitative way the concepts of scaling and pre-scaling. In the third chapter the theoretical framework is presented. In this chapter the research gap and the hypotheses are deeply analysed focusing on the theoretical explanation behind their formulation. The fourth chapter provides an explanation of the method we employed to carry out the analysis, focusing on the research design, the characteristics of the sample and the operationalization of the variables. The fifth chapter deep dives into our empirical analysis focusing on the econometric models used and the results we achieved. The sixth chapter concludes our analysis by providing key findings, limitations, theoretical and practical implications of the results.

2 Literature review

2.1. Human Capital Theory

2.1.1. Research process

Nowadays, almost all companies' activities and processes rely on information and knowledge, making human capital a crucial component of modern economies. As a result, vast research has been conducted over the last few decades on the process of investing in and acquiring human capital, especially in newly founded ventures.

In order to find relevant literature about human capital and human capital entrepreneurship research, we used a search method known as **snowballing**. Snowballing is the practise of identifying additional papers by leveraging a paper's reference list or citations; the use of references and citations is referred to as **backward and forward snowballing,** respectively (Wohlin, 2014).

Specifically, we first relied on Google Scholar to gather a start set of papers around the topic to use for the snowballing procedure. Human capital and entrepreneurship keywords were used to collect studies (e.g., human capital, education, training, knowledge, skills, ability, competence, entrepreneur, entrepreneurship, new venture). After reviewing the selected articles, we chose as our start set the following two highly cited human capital's literature reviews: "A review of human capital theory: Microeconomics" of Fleischhauer (2007) and "Human capital and entrepreneurship research: A critical review and future directions" of Marvel, Davis and Sproul (2016).

These publications enabled us to reach an understanding on the current state of the research subject. We extracted as much information as possible and then we started conducting backward snowballing. We manually went through the reference list of the five papers and looked for potential articles to be included in our literature review based on some basic criteria, such as title, publication venue and authors. Articles were considered only if they were published in renowned scientific journals or by well-known field researchers. After this first screening, we verified the content of the candidate papers and made the ultimate decision to either include or exclude them.

Contributions from management-specific journals include: Strategic Management Journal (1), Academy of Management Perspectives (1), Administrative science quarterly (1), Academy of Management Journal (1), Academy of Management review (1), IEEE Transactions on engineering management (1). Articles from economic journals include: The economic journal (1), Journal of political economy (4), Journal of economic literature (2), The American Economic Review (1), Journal of monetary economics (1), The American economic review (1), Southern Economic Journal (1). Articles that were derived from entrepreneurship-specific journals include: Journal of Small Business Management (2), Journal of business venturing (4), Entrepreneurship Theory and Practice (1).

2.1.2. The concept of Human Capital

Human capital theory emerged as an area of study in the early 1960s, when economists noticed that they were struggling to explain the growth of the US economy in terms of the primary traditional factors of production (i.e., land, labour, and tangible capital inputs) (Nafukho et al., 2004). This discrepancy between explained inputs and the ultimate outcome was defined as a statistical "measure of our ignorance" by Abramovitz (1956); later, it was referred to as "**residual factor**" and identified as "**human capital**" by Schultz (1961). Denison was the first economist to formally add education into the production function model. He estimated human capital investment to be responsible for at least 43% of US economic development from 1929 to 1957.

Human capital can be defined as “the knowledge and skills that people acquire through education and training being a form of capital, and that this capital is a product of deliberate investment that yields returns” (Schultz, 1961). According to human capital theory, people's learning skills are as worthy as other resources involved in the creation of commodities and services (Lucas, 1988). Therefore, an individual's or a firm's decision to invest in human capital (i.e., conduct or fund more education or training) is comparable to those regarding other sorts of investments.

Human capital is composed of three major elements (Blundell et al., 1999): (a) **Early ability** (whether acquired or natural); (b) Qualifications and knowledge acquired through **formal education** (in which the individual commits his whole time to learning); (c) Skills, competencies, and expertise acquired through **training**. Training may be subdivided into two categories: on-the-job training (in which the current employer provides post-school training), and off-the-job training (i.e., post school training provided by "for-profit" proprietary) (Fleischhauer, 2007).

Empirical evidence indicates a strong linkage between diverse types of human capital investments (Blundell et al., 1999). Indeed, early accomplishments and qualifications are significant factors that influence future educational attainment; family background (e.g., average household income, parents' education level, and the number of siblings), and local environment (e.g., opportunities in the local unskilled labour market, the quality of local schools, and closeness to a college) have a great influence too. In turn, more educated individuals undertake more on-the-job training, and individuals who have previously engaged in training are more inclined to take part in more training (Blundell et al., 1999).

Human capital investments include an **upfront cost** (e.g., tuition and training course fees, foregone earnings while in school, lower salaries and productivity throughout the training time), and they provide people, companies, and society with returns that are difficult to quantify precisely. As with physical capital investments, individuals invest in schooling and training until the returns in extra income equal the expenses of participation; returns are both **private** to the individual, in the form of higher salary, and **public** to society, in the form of increased productivity supplied by the educated (Becker, 1964).

Weisbrod (1961) conveyed the relationship between human capital investments and productivity devising a conceptual framework in which the present value of an individual at any given age a is defined as the total of his discounted projected future earnings Y_t (equivalent to the value of productivity):

$$V(a) = \sum_{t=a}^{\infty} \frac{P_{at}}{(1+r)^{t-a}} Y_t$$

P_{at} represents the probability of an individual of age a to be alive at age t and r is the discount rate.

2.1.3. Human Capital and Entrepreneurship Research

Human capital theory has been progressively applied in entrepreneurship over the last few decades, incorporating skills and abilities that are valued in this domain (Marvel et al., 2016).

According to human capital entrepreneurship research, human capital factors influence the transition from one stage of the entrepreneurial process to the next, even though a form of human capital required to achieve one milestone may be less critical, or even detrimental, to subsequent milestones (Marvel et al., 2016).

The significance of knowledge and experience in recognizing and reaping the benefits of entrepreneurial opportunities is highlighted by both the discovery theory and the creation theory. Exploiting discovery opportunities, for instance, typically relies on the individual's prior knowledge of markets and goods, whereas exploitation of creation opportunities depends on the individual's expertise in guiding the execution process (Alvarez and Barney, 2007). According to Kirzner (1973), opportunities are identified through entrepreneurial alertness, which is higher in serial and portfolio entrepreneurs thanks to their experience (Westhead et al., 2005). Even though human capital components are key for entrepreneurial discovery, it is still unclear if this is due to cognitive differences, increased self-confidence, or fewer perceived risks since if their venture failed, they would be more readily reabsorbed by the labour market (Davidsson and Honig, 2003).

Furthermore, human capital attributes are a critical resource for start-ups' survival and growth (Florin et al., 2003). They are especially crucial in the early years of a company, when founders must overcome cognitive hurdles and adapt to unexpected conditions that may necessitate quick decisions and actions. High human capital aids them in learning new tasks as well as adapting to changes. Owners of established firms, instead, have routines and standard procedures to which they may refer (Unger et al., 2011). Moreover, human capital components such as the entrepreneur's reputation, competence and dedication are beneficial in securing financial and physical resources (Brush et al., 2001). Indeed, venture's human resources can mitigate external stakeholders' uncertainty by acting as a signal of capability and trustworthiness. Potential investors initially lack reliable evidence about the quality of the product or service being supplied as well as the actual market size (Florin et al., 2003). As a result, the judgment of business potential and subsequent decision to invest is impacted by a variety of factors surrounding the enterprise, including team competencies (furthermore, the attractiveness of the product/service, market dynamics, and prospective profits if the venture is successful are assessed). When it comes to entrepreneurs' characteristics, the most commonly employed selection criteria are managerial abilities and experience (Zacharakis and Meyer, 2000).

Human capital may have a greater relevance in high-tech, knowledge-intensive industries, as knowledge lowers perceived uncertainty related to innovation and dynamic contexts (McMullen and Shepherd, 2006). Superior human resources may also improve a start-up's dynamic capabilities as well as its ability to achieve, maintain, and even enhance its competitive advantage (Florin et al., 2003).

Overall, research suggests that higher human capital leads to grater entrepreneurial success (Unger et al., 2011). However, highly educated individuals may choose not to engage in entrepreneurial activities since the projected incomes are lower than those of alternative career opportunities (Cassar, 2006). Indeed, given their human capital, individuals choose an employment that maximizes the current value of economic and psychic benefits across their lifetimes (Gimeno et al., 1997). Individuals with high human capital are valued more by the labor market and receive higher wages commensurate with their abilities, owing to enhanced productivity as a result of human capital investments. As a result, they incur larger opportunity costs, namely the income that can be earned through paid work rather than through entrepreneurial activity. Therefore, if they decide to launch a start-up, these individuals are likely to aim for greater growth and profitability in order to earn a remuneration commensurate with their opportunity costs (Cassar, 2006).

2.1.4. General and Specific Human Capital

Becker (1964) categorises human capital into two types: general and specific human capital. **General human capital** may be easily applied in many settings, and consequently it is valuable to both present and prospective employers; it refers to basic knowledge acquired by individuals via formal education and professional experience (Colombo et al., 2004). **Specific human capital**, on the other hand, boosts a worker's productivity only in limited settings, such as experience or technical skills acquired in a particular sector.

In the entrepreneurial setting, specific human capital is closely related to the industry-specific skills that founders learned in the organisation where they were previously employed, as well as the leadership experience gained through a managerial position in another firm or prior self-employment; therefore, it refers to the skills that can be directly applied in a newly formed start-up. Previous research has demonstrated that the specific component of founders' human capital has a positive impact on the survival chance and the growth rate of new enterprises, since individuals with higher degrees of specific human capital usually perform better as entrepreneurs and are more confident in their entrepreneurial abilities (Colombo et al., 2004).

2.1.4.1. Firms’ Investments in General and Specific Training

According to Becker (1964) in competitive labour markets where workers receive their marginal product of workers, firms are unwilling to pay for general training since they would not be able to recoup their investment. Indeed, if trained employees left their jobs, general training would be equally beneficial across numerous companies, raising wage rates and marginal products by the same amount in all of them. As a result, firms providing such training could not capture any of the return. Employees getting general training, on the other hand, have an incentive to bear these expenditures since training increases their future productivity and wage. Trainees can finance such cost by accepting wages below their productivity during the training period. As a result, if they are not credit constrained, they may invest efficiently in the accumulation of general human capital.

Acemoglu and Pischke (1999) argue that some evidence undermines the assumptions of Becker's training theory. Indeed, there are situations in which companies pay for general training: firm-sponsored training emerges as an equilibrium phenomenon when labour markets are imperfect, and worker's compensation is lower than his marginal product. In this case, general training may be firm-sponsored as the **wage structure is compressed** (i.e., there is only a small difference in pay among employees regardless of their skills, experience or seniority). Wage compression implies that the wage function increases in the level of training less sharply than productivity, resulting in a larger gap between productivity and wage at higher competence levels; as a result, the return on skills for a worker is lower than in a competitive labour market and firms prefer employing more skilled workers (in competitive labour markets, instead, earnings from skilled and unskilled workers are equal, so firms are indifferent about employees' ability level). Companies may therefore decide to invest in their workers' skills in order to boost their profitability.

There are various causes of labour market imperfections that result in a compressed wage structure and therefore in firm-sponsored training (Acemoglu and Pischke, 1999). For instance, an important source of wage compression is the presence of **asymmetric information** between the current firm and other potential employers. Indeed, potential employers may not be able to observe the actual quantity and content of the training the worker has received; consequently, they may be reluctant to reward workers for these uncertified abilities, allowing the current company to retain trained individuals paying them a relatively low wage. In this situation, a gain in productivity does not convert into a rise in wages, so that the equilibrium wage structure will be compressed. Moreover, potential employers may not be aware of a young worker’s natural abilities, which might disclose important information about his suitability for the career he has undertaken. When ability and training are complementary, so that high ability employees profit more from training, information asymmetry leads to a compressed wage structure and motivates employers to sponsor training. Indeed, as a highly skilled worker cannot quit if he wants to signal his ability, the employer may retain him and pay less than the full value of his skills.

Finally, in terms of specific training, this form of training increases employee productivity solely in the firm making the investment, thus the salary he may earn elsewhere is unrelated to the amount of training he received. According to Becker (1964), firms in both perfect and imperfect labour markets are willing to bear specific training costs. Indeed, they would reap the benefits of such training in the form of higher profits as a consequence of increased productivity. Furthermore, employers may improve staff retention by paying higher wages following training — in other words sharing some of the return from training with trainees. The final step would be to share also training expenses with employees, bringing supply closer to demand.

Becker (1964) further emphasises that workers' or firms' willingness to pay for specific training is directly related to the likelihood of labour turnover. On one hand, if a company had paid for specific training for a worker who decided to quit his job, its investment would be partially lost because no additional return could be obtained. On the other hand, a worker fired after having paid for specific training is unable to collect any further return and suffers a capital loss.

2.1.5. Human Capital Investments

Education and training are the most critical human capital investments (Becker, 1964). They are viewed as purposeful expenditures that raise **human productivity** and thereby **organisational profitability**, and they are both key drivers of **economic growth and development** on a global scale. Moreover, education and training tend to limit population growth while simultaneously enhancing overall quality of life. Educated people are more involved in democratic institutions, thus increasing **social cohesiveness**; moreover, they can adapt to new activities and technology more quickly and efficiently, and it has been proven that they are a direct source of **innovation** (Blundell et al., 1999).

Human capital literature has advanced along two paths (Haley, 1973): the first, based on Becker, evaluates individual investment in human capital and tries to determine the internal rate of return to that investment, whereas the second, based on Ben-Porath, deals with the life cycle of earnings.

2.1.5.1. Internal rate of return

Some actions have a greater influence in the present, while others impact mainly future well-being (Becker, 1962). When people engage in human capital expenditures, they look forward to **future pecuniary and non-pecuniary returns**, not to immediate pleasures. Activities that impact future income through imbedding resources in individuals may be considered investment rather than consumption, given that the latter provides limited future benefits (Blaug, 1976). Indeed, education and training are investments of time and missed earnings in exchange for higher future rates of return (Becker, 1964).

Bowen (1964) identifies two perspectives of the returns-to-education approach: (a) the personal profit orientation; and (b) the national productivity orientation. The former supports individuals in determining the appropriate level of education to accumulate by analysing differences in lifetime earnings as evidence of personal financial benefit due to educational investments (i.e., it measures the rate of return in terms of an individual's additional earnings for an extra year of schooling and training). The latter, on the other hand, investigates whether society invests the appropriate share of resources in education by focusing on differences in lifetime earnings relative to educational attainment as an indicator of how education investments impact national productivity (i.e., it investigates whether the level of education in a cross-section of countries is related to GDP growth rates).

According to Mincer (1974), the logarithm of earnings is linearly dependent on the years of schooling (if the only expenditure of an additional schooling year are foregone earnings and the proportionate income rise is constant across one's lifetime). This results in the following equation for the individual i:

$$lnW_i = \beta_0 + \beta_1 S_i + \beta_2 X_i + \beta_3 (X_i)^2 + \varepsilon_i$$

Individual i's salary is denoted by W_i, S_i is the number of years of schooling, X_i is a measure of job experience, and ε_i is an individual disturbance term independent of β_0 and S_i. To reflect the concavity of the earnings profile, work experience is included as a quadratic variable. Finally, parameter β_1 represents the rate of return on educational investments.

By estimating this equation on cross-sectional data from the 1960 US census, Mincer (1974) found that an additional year of full-time schooling yields a net increase of 11.5% in annual earnings. Using OLS, the equation was then estimated for several more countries. Although the rate of return varies significantly depending on many influencing factors, such as the type of acquired skill and certification earned, the average estimate for developed economies generally ranges from 5% to 10%, with slightly larger estimates for women than men (Wilson, 2001).

2.1.5.2. The life cycle of earnings

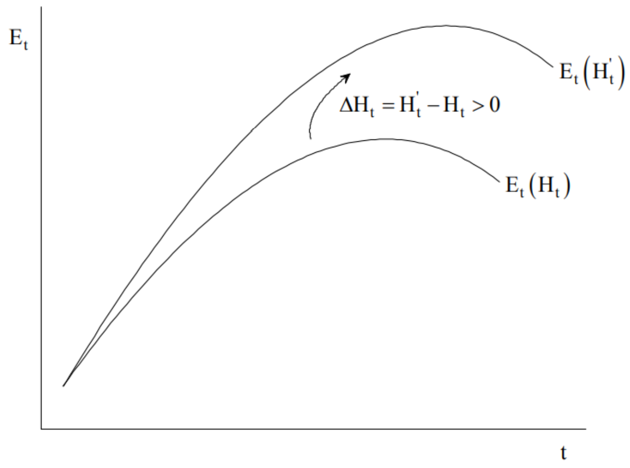
Another important body of literature focuses on the life cycle of earnings. According to **Ben-Porath** (1967), there are three phases of human capital accumulation: (a) an initial phase with no earnings (i.e., full-time human capital production, known as "formal schooling"); (b) a long phase with part-time human capital production, characterized by earnings increasing with age but at a declining rate and eventually decreasing (Becker, 1964); and (c) a third phase with no training. At any point in time, individuals with more schooling or greater ability invest more in on-the-job training.

Models of human capital accumulation across the life cycle may be divided into two categories: **earnings maximizing models** and **utility maximizing models (**Fleischhauer, 2007). Earnings maximizing models only analyse the trade-off between investment and income: when the individual tries to maximize his discounted future earnings stream, he faces a trade-off between producing additional human capital and renting his existing stock of human capital in the labour market. Utility maximizing models, instead, also incorporate the labour-leisure choice so that labour supply becomes endogenous to the model.

According to Becker (1962) human capital investments decline with age, due to the fact that younger people receive the benefits of schooling over a longer period of time, and investment risk increases with age. As a result of decreasing marginal returns and increasing marginal costs, the optimal stock of human capital investment is negatively related to age (Mincer, 1970). However, if the acquired human capital is specific, human capital investment may not diminish monotonically with age: while the profitability of general skills is determined by the length of one's working life, the profitability of specific skills is influenced only by the predicted duration of one's present employment (Bartel and Borjas, 1977).

Mincer (1958) observes that the gap between regularly distributed abilities and positively skewed income distributions must be attributed to expenditures in human capital during the life cycle. His empirical findings about individuals' age-earnings profiles (1970) are illustrated in Figure 2.1. Earnings (E_t) are positively related to the stock of human capital (H_t) at date t; the age-earnings profile is concave and upward sloping for a long time. When human capital investment rises, the age-earnings profile steepens and peaks later.

Figure 2.1: Human Capital and the Life Cycle of Earnings (Fleischhauer, 2007)



2.1.6. Outcomes of Human Capital Investments

According to Becker (1964), human capital investments result in knowledge and skills. As a result, the majority of studies have used education or job experience as proxies for entrepreneurs' human capital (Reuber and Fischer, 1994). In the literature, education is commonly operationalized by years of study or the acquisition of a university degree, whereas professional experience is typically characterized by years of working experience prior to establishing the new firm or previous managerial roles held. Types of education (e.g., engineering, social sciences, etc.) and professional experience (e.g., R&D, marketing and sales, etc.) are also discussed because they may have diverse effects. Previous entrepreneurial experience is another common indicator, which is usually operationalized using dichotomous variables, followed by age, gender, and if family members were entrepreneurs (Marvel et al., 2016).

However, past experience metrics may be inadequate indicators of human capital since they involve the unrealistic assumption that all people learn at the same pace and that all circumstances classified in a similar manner are equally rich learning settings. Actually, whether or not experience leads to knowledge is determined by the characteristics of the individual and the environment (Reuber and Fischer, 1994). The transformation of experience into knowledge and skills is referred to as human capital **acquisition** (Unger et al., 2011). Furthermore, human capital contributes to greater performance only when it is effectively transferred to the specific activities that must be completed (Reuber and Fischer, 1994). The application of knowledge acquired in one context to another is referred to as human capital **transfer** (Unger at al., 2011).

As a result, it is worthwhile to distinguish human capital investments from outcomes of human capital investment: human capital investments may or may result in outcomes of human capital investments, whereas outcome-based human capital constructs are direct predictors of human capital (Unger et al., 2011).

Marvel et al. (2016) identify three main categories of human capital outcomes**.** **Knowledge** is the ownership and comprehension of principles, facts, processes and their interrelationships, and it is more valuable when it is domain-specific. It can be acquired by investing in education, training, and experience, as well as recruiting key personnel. Besides, prior knowledge facilitates the acquisition of new related knowledge (Cohen and Levinthal, 1990). **Skills** are visible applications or know-how and are typically task-specific. They are not necessarily permanent, and their effectiveness is determined by experience and practice. Finally, **abilities** differ from skills because they are less likely to change over time, and they may be used across a diverse range of tasks that may be encountered in a variety of circumstances. They can be gained through investing in team members, alliances, and organizations.

In Figure 2.2, the main dimensions of human capital investments and outcomes are highlighted:

Figure 2.2: Dimensions of human capital investments and outcomes (Marvel et al., 2016)

	Investments	Outcomes
Impart	Education – investments in learning activities of explicit knowledge. ▪ Vary from general to specific types of education. ▪ Vary in cost, diversity, and length of investment.	Knowledge – understanding of principles, facts, and processes. ▪ Clustered within domains such as those learned through formal education. ▪ Vary from generic to specific.
Develop	Training/experience – investments in learning by doing activities. ▪ General or specific to context (e.g., industry) or task (e.g., prototype development). ▪ Vary in terms of cost, amount, time, and type.	Skills – observable application of knowledge to create solutions to problems or complete specific task. ▪ Specialized or domain specific skills (e.g., industry or task-specific). ▪ Vary in type from novice to expert.
Acquire	Recruitment – Investments in recruitment activities to acquire abilities. ▪ Sources may include venture team, firm alliances, network ties, external R&D, etc. ▪ Vary in cost, form, and quality.	Abilities – Enduring, trait-like characteristics useful to range of tasks. ▪ More general with implications to wide range of contexts and tasks. ▪ Difficult to internally develop compared to knowledge or skills.

2.2. Common ground

2.2.1. Research process

The literature review about common ground was conducted through the method of backward snowballing using the web search engine Google Scholar. The research was carried out by combining the following key words: *common ground, mutual knowledge, coordination system, tacit coordination mechanisms, prior shared experiences, workgroup*. We selected 2 papers from *Strategic Management Journal*, namely Zheng et al. (2016) and Srikanth and Puranam (2011); 2 papers from *Organizational Science*, namely Cramton (2001) and Srikanth and Puranam (2014) and the work of Clark (1996) to start the process of backward snowballing. We selected papers that address the concept of common ground and coordination from a managerial and organizational perspective, then we examined the topic from a psychological and social perspective. Moreover, using the work of Ruef et al. (2003), we reviewed some theories behind the formation of an entrepreneurial founding team (EFT). This allowed us to learn more about how the idea of common ground influences the development of an entrepreneurial venture and facilitates team collaboration.

Through this approach, we are able to understand the nuances underlying the concepts of coordination and shared experiences, which are typically only discussed from a theoretical standpoint. Indeed, it appears difficult to measure the idea of common ground since it raises several challenges on its quantification. However, approaching the idea from a psychological perspective gives this study an all-round perspective that might aid in understanding the idea of common ground.

2.2.2. Formation of an entrepreneurial founding team and coordination

The formation of a team can be analysed through the interpersonal and attraction perspective (Forbes et al., 2006). In order to work together and make strategic decisions together, the members of an EFT must succeed in communicating and coordinating the various activities. Indeed, the fit among them is a crucial aspect to make strategic decisions together and thrive the business model of the venture. Thus, this perspective takes into account socio-psychological theories that assess the boundaries among peers.

The work of Ruef et al. (2003) deepens this stream of literature by analysing the team formation through the concept of **homophily**. EFTs tend to be formed by similar individuals in terms of ascriptive characteristics (e.g., gender, age and ethnicity), achieved characteristics (e.g., work experience and education) and internal psychological states such as values and beliefs. These aspects enhance a higher level of understanding and trust among team members. So homophily can be seen as the natural tendency to have an EFT composed by homogeneous members coming from the same contexts.

The second concept that Ruef et al. (2003) tackles is the **social network mechanism** that influence the EFTs' formation. The interaction with individuals that can happen in different contexts such as the workplace or the university, gives the possibility to observe how peers think and to observe their skills. Beside the concept of observation, the continuous interaction helps to develop mutual trust among individuals and give the chance to spot possible team members for future businesses. This is one of the possible reasons that lead to the creation of EFTs among family members, friends and prior colleagues. On the positive side the presence of prior ties among team members enables an easier communication and coordination while on the negative side this phenomenon could lead to knowledge gaps and difficulties when dealing with problematic issues.

Concepts of homophily and social networks can be seen as expressions of a broader concept that encompasses an innate tendency to look for shared characteristics, ideas, or life experiences in others. Indeed, finding a point of commonality between two people can help people communicate more effectively and understand one another better, and that can improve coordination.

In fact, coordination among peers is a major issue in all types of enterprises, but notably in start-ups, and it may undermine all types of tasks by wasting a significant amount of time.

Coordination depends on three distinct factors that are critical to the performance of any task (Klein et al., 2005): first, interpredictability, namely the ability to reasonably predict the activities of other peers; second, directability, or the ability to monitor and adapt to the activities of another team member (Christoffersen and Woods, 2002); third, common ground, which allows people to adopt shorter forms of communication while being relatively certain that potentially ambiguous messages will be understood (Klein et al., 2005).

The notion of common ground is the essential ingredient for a fruitful exchange of information and it is built upon shared experiences and knowledge. However, before providing the proper definition, it is necessary to grasp the nuances that distinguish between shared knowledge and mutual knowledge, which are the roots of the notion of common ground.

2.2.3. Shared Knowledge

Clark and Marshall (1981) provided the first formal definition of shared knowledge. In their work, they consider two candidates and a specific proposition p that, in the view of the candidates, reflects a shared opinion about a topic (for instance, p could be the sentence “Titanic is an awesome film”). Then, Shared Knowledge can be theorized as follows:

A and B share1 knowledge that p = def.

(1) A knows that p.

(1’) B knows that p.

Furthermore, if both candidates know that they share knowledge it means that each of the two knows that the other knows the statement p:

A and B share2 knowledge that p = def.

(1) A knows that p.

(1’) B knows that p.

(2) A knows that B knows that p.

(2’) B knows that A knows that p.

This reasoning can be infinitely iterated until sharedn knowledge with (n) and (n') statements is reached.

2.2.4. Mutual Knowledge

According to Clark and Marshall (1981), Lewis (1969) was the first academic to establish the notion of Mutual Knowledge, although he titled it Common Knowledge. Then, Schiffer in 1972 provided the following definition of Mutual Knowledge:

A and B mutually know that p = def.

(1) A knows that p.

(1’) B knows that p.

(2) A knows that B knows that p.

(2′) B knows that A knows that p.

(3) A knows that B knows that A knows that p.

(3′) A knows that B knows that A knows that p.

Et cetera ad infinitum.

Therefore, Schiffer referred to Mutual Knowledge as Shared∞ Knowledge (Clark and Marshall, 1981): indeed, we can think of Mutual Knowledge as a broader concept that encompasses the idea of Shared Knowledge.

The following definition of Mutual Knowledge was offered by Harman (1977), who improved upon the previous concept of Schiffer (1972) by introducing the general proposition q that incorporates all the previous iterations:

A and B mutually know that p = def.

(q) A and B know that p and that q.

Finally, Clark and Marshall (1981) combined the previous contributions into the Mutual Knowledge formula shown below:

A knows that A and B mutually know that p.

So, by combining all the premise statements from Schiffer's (1972) definition into a single recursion, the authors were able to completely ignore all the premise statements providing a leaner definition.

Leaving the formal domain, Mutual Knowledge can be considered as the knowledge that the communicating parties share and are aware of sharing it (Krauss and Fussell, 1990). Mutual knowledge involves not just the information itself, but also the information that the other person is aware of it, which increases the likelihood that the information will be understood (Cramton, 2001). Without Mutual Knowledge, a peer may misinterpret what the other says about a situation owing to different premises upon which the judgement is founded (Blakar, 1985).

Based on this notion, Krauss and Fussell (1990) discovered that Mutual Knowledge can come from three different sources:(a) Direct Knowledge, namely the ability to infer what one knows and does not know from experiences that have been shared with them and through personal observation of their behaviours and environment; (b) Interactional Dynamics, which means that Mutual Knowledge may be established through interaction of two peers; (c) Category Membership, which implies that people mature Mutual Knowledge simply by making assumptions about others' knowledge based on the social categorizations they apply to them (Clark and Marshall, 1981; Krauss and Fussell, 1990). In other words, you assume that the interlocutor had experiences that are essential to understand the context of what you are saying. For example, we expect that a florist knows the difference between roses and daffodils, thus we rely on this knowledge when asking the composition of our bouquet.

2.2.5. Common ground

2.2.5.1. A definition of common ground

Herbert H. Clark is a well-known communication theorist who formalized the concept of **common ground**. He defined it as the sum of mutual, common, or shared knowledge, beliefs, and suppositions. So, it is a type of self-awareness, self-knowledge, self-belief, and self-assumption in which there is at least one other person who possesses a similar level of self-awareness (Clark, 1996). This idea incorporates all the above definitions of knowledge by emphasizing the idea of information rather than the previously mentioned formal distinctions.

Common ground may be classified in two types: (a) **communal common ground**, which is based on the cultural groups to which a person is deemed to belong (nationality, occupation, ethnic group and gender); and (b) **personal common ground**, which is instead the knowledge based on personal acquaintance, that is scarce among strangers but abundant among intimates.

To appreciate how significant this notion of common ground is, notably in the development of a new firm, it is necessary to examine its relationship with the concept of trust among team members. Indeed, having a well-established common ground among peers is crucial, especially given the unforeseen situations that may arise during the rowdy years of a start-up. In the face of unforeseen events, a lack of common ground can lead to a severe decline in trust among team members.

In particular, the degree of communal common ground influences the perception of initial trust – as previously stated, humans have a natural inclination to categorize strangers into stereotypical communities while automatically appraising them through communal common ground, while personal common ground (built through shared experiences) determines whether or not that initial trust will persist (Priem and Nystrom, 2014).

Furthermore, people evaluate the common ground with the intended audience in each conversation and adjust what they say accordingly (Fussell and Krauss, 1992). Indeed, they rely on Speaker Presuppositions, that are estimations of common ground that are frequently taken for granted by speakers. The validity of these assumptions influences whether and how messages are interpreted by the audience (Stalnaker, 2002).

Common ground also affects task performance and viability by increasing their value. In this regard, Balkundi and Harrison (2006) discovered that teams with strong interpersonal connections (i.e., a manifestation of Personal Common Ground) achieve their goals better and are more committed to stick together. Their study also shows that teams perform better when their leaders are central in an intrateam network and when they are central in an intergroup network as a whole.

2.2.5.2. Common ground and coordination in the industrial world

In general, languages, dialects, jargons, cultural standards, processes, ineffable sights, sounds, and sensations are all ways for people to connect (Clark, 1996). These differences can provide a significant barrier to communication in a variety of situations by hampering the proper flow of information from one peer to another. A declension of the issue raised by Clark concerning different language and dialects can occur in the industrial word, for example through the know-how of products and processes along the value chain of a company.

In this regard, Bechky's (2003) study examines how employees solve challenges by co-creating common ground that affects their knowledge about both the product and the manufacturing process. The understanding gap between two peers is caused by decontextualization, which is the context-based usage of various words and concepts to discuss the same topic. Therefore, the degree to which two speakers have common ground influences the effectiveness of their communication.

When members lack in common ground, more communication effort is necessary for coordination, and the chance of communication mistakes increases (Fast et al., 2009; Krifka, 2004). To overcome misjudgments, people from various groups must gather and debate on the issue at stake in order to bring alternative perspectives and solutions to the problem. As a result, creating common ground from the dialogue of the two parties allows coordination and the avoidance of future misunderstandings.

This attitude towards the development of common ground is especially important when peers participate in Joint Activities. For achieving success in this kind of activities, parties must be keen on collaborating and their work must be interdependent (Clark, 1996; Klein et al., 2005). Furthermore, the Joint Activity needs a "Basic Compact," which represents a degree of commitment of all participants to support the coordinating process. More precisely, the Basic Compact is a commitment (typically unspoken) to engage in the shared activity and to carry out the necessary coordinating duties (Klein et al., 2005).

The amount of common ground required for the Joint Activity varies depending on the situation and the nature of the coordination mechanisms used. There are several coordination mechanisms that facilitate in the formation of enough common ground so that coordination takes place (Priem and Nystrom, 2014). Ongoing Communication is the simplest one, which consists in updating continuously and dynamically the Common Ground to achieve coordination. Modularity, on the other hand, is a coordination mechanism that involves the division of activities into modules, the assignment of peers to the different modules, and the creation of interfaces that are part of individuals' common ground. This way, coordination is achieved to the right interpretation of the interfaces. Tacit Communication Mechanisms (TCMs) allow for the formation and usage of common ground without the relying neither on direct, ongoing communication nor on the development of modular interfaces. It builds common ground through observation of the work context, actions, and outcomes, rather than direct communication, by leveraging preexisting common ground that may not be specific to the task at hand (Srikanth, Puranam, 2011; Srikanth, Puranam, 2014).

2.2.5.3. Knowledge transformation and ICT

A further step towards the understanding of Common Ground comes from Interactional Dynamics (previously mentioned in chapter 2.2.4). Indeed, to create common ground, individuals must go through a process of **knowledge transformation**, which is derived by the convergence of various experiences and understandings of reality. When a meaning, frame, or vocabulary is defined in an enclosed area (e.g., a division of a company, a household, etc.), it may spread throughout a population of interacting agents until the entire community shares the new vocabulary or frame. Consequently, the construction of a common ground is an emergent process rather than the result of a precise planning (Cornelissen and Werner, 2014). Interaction between members of various communities transforms the groups' local understandings into deeper, more generally shared understandings. This process happens anytime a member of one community comes to comprehend how information from another community falls within the framework of his own activity, enhancing and changing what he knows (Bechky, 2003; Krauss and Fussell, 1990).

Furthermore, it is known that an effective information exchange, which is at the basis of knowledge transformation, requires a complete sharing of perspectives. The use of technology to communicate can hamper this process, since typing on a device eliminates all the nuances that come with paraverbal and nonverbal communication (Hightower and Sayeed, 1995). Besides, in terms of updating common ground, ongoing communication in virtual contexts using information and communication technology (ICT) is inadequate compared to face-to-face communication. Indeed, virtual communication is inefficient at arranging complex, ill-defined tasks with high interdependence (Srikanth, Puranam, 2014).

To sum up, on one hand the implementation of the right coordination mechanism (as mentioned in the previous chapter) may enable knowledge transformation and thus, the creation of common ground among peers; on the other hand, common ground can be hampered by the deployment of tools for virtual communication.

2.2.5.4. Prior Shared Experience (PSE)

Another relevant research stream tackles the concept of **Prior Shared Experience (PSE)**. Zheng et al. (2016) use this term to refer to all the work experiences that some or all founding team members had before launching their new venture. Indeed, a prior industry experience is a precious source of human capital for new ventures, which usually have scarce resources in the initial stages. In this context, the founders' activities have a direct impact on business performance, making their market knowledge even more important for the survival of the company compared to established businesses (Helfat and Lieberman, 2002; Ucbasaran et al., 2013). Yet, these prior experiences become even more important if they are shared among team members.

To emphasize the significance of this concept, it has been demonstrated that joint work history is associated with faster product delivery to markets (Beckman, 2006) and higher startup performances (Eisenhardt and Schoonhoven, 1990). PSE enables the creation of common routines and the understanding of tasks. Furthermore, it aids in the interpretation and interaction with the environment by reflecting the similarity and accuracy of knowledge held by founding team members (Klimoski and Mohammed, 1994; Walsh, 1995; McIntyre and Foti, 2013).

According to the findings of Zheng, Devaughn, and Zellmer-Bruhn (2016), teams with any PSE outperform teams without PSE as current shared experience increases. Nonetheless, we are far from concluding that more PSE is always better than unshared experience, since a founding team may inherit inappropriate industry knowledge in some cases.

To conclude, we may think of PSE as another definition of common ground, and its measurement can be linked to the concept of PSE Extensiveness. This notion will be further elaborated in Chapter 5.5.2.

2.3. Scaling

2.3.1. Introduction

In our culture, it is frequently discussed how successful and ambitious start-ups are in offering cutting-edge goods and services. Start-ups now play a crucial role in our economic system by fostering innovation and advancement across all fields of knowledge. Nowadays, scholars investigated for the majority early-stage start-ups and ventures in general, providing few research about the topic of scaling. Even though, the start-ups that can make it through the early stages and expand their businesses have a greater chance of bringing real innovation to society. As a result, we attempted to investigate this little-known stage that somehow represents the actual group of candidate ventures that can succeed and that can generate a significant share of new jobs in an industry (Birch and Medoff, 1994). This chapter tries to define the start-up lifecycle and discuss the definitions and metrics that are currently used in the literature to describe the scaling phase. Then, it focuses on one specific stage: the pre-scaling phase. Indeed, by offering metrics that can help to frame this particular phase, we will attempt to describe some aspects of this stage.

2.3.2. Research process

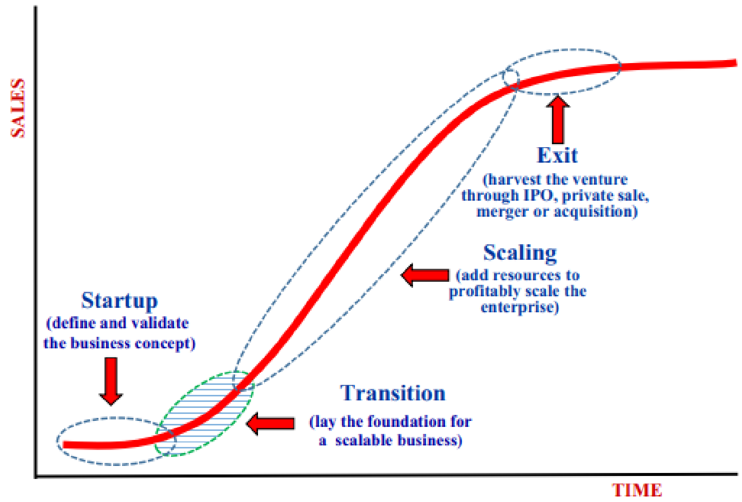
This literature review was conducted by analyzing 159 papers. The research started on Scopus by searching papers using the keywords *scale-up, scaleup, scalability* and *scaling*. The set of keywords for *scaling* has been identified to capture papers explicitly treating the topic, besides the ones that address the topic of growth. The forehead mentioned keywords were combined with a set of keywords for *entrepreneurial ventures* (i.e., *entrepreneurial venture, new venture, young venture, new firm, young firm,* *startup, start-up, scaleup, scale-up*). Then, the pool of papers was filtered by selecting the subject areas of *economics, econometrics and finance* and *business, management and accounting*. We gathered more than 200 potential papers on the subject of scaling and growth from this primary research. We narrowed down the potential papers from this pool by choosing 159 papers that address entrepreneurship-related topics. Moreover, we integrated our work by adopting a backward snowball sampling technique to unearth some further hints about scale-ups' literature.

The goal of this chapter is to examine the stage of research that had been done on our unit of study, namely entrepreneurial ventures in phase of pre-scaling. The work begins by analyzing the scaling phase, a topic that has received more attention in the literature rather than the pre-scaling. Thus, in the next chapters we provide a summary of the scale-up stage metrics cited in the literature.

2.3.3. Start-up's life cycle

To understand the concept of scale-up, we must first define the stages of a venture's life cycle. Picken (2017) provides a model that is tailored on the creation of an entrepreneurial venture by evolving the model of Steinmetz (1969) applied to small businesses. The model specifies four stages of business development: **start-up**, **transition**, **scaling**, and **exit** (see Figure 2.3). When an entrepreneur has gained some traction in the market and is striving to provide resources and expertise for a rapid scaling, the transition phase begins. This stage appears to match the pre-scaling phase precisely, according to our intuition. Indeed, a venture at this stage should concentrate on amassing all the resources required to move on to the next phase, where the high growth can occur. As a result, we can move on to the definition of scale-ups as ventures that have already reached the Pickens-mentioned scaling phase (2017). Other models for interpreting the lifecycle of a venture are also put forth by academics. For instance, Huynh et al. (2017) claim that a newly formed venture can be divided into two phases: the creation phase, which includes idea generation, proof of concept, and business plan setting; and the growth phase, which includes commercialization of the product/service and market entry. As an alternative, Marmer et al. (2011) offer a framework with six stages: discovery, validation, efficiency, scale, sustain, and conservation. In general, we recognize that researchers found at least one stage that has to do with the expansion or scale of a venture. In this work we will rely on the framework of Picken (2017) trying to provide further details about the transition and scaling phase.

Figure 2.3: Stages of business development (Picken, 2017)



2.3.4. Start-up's definition

First, we must comprehend what a start-up is in order to understand the stages that are mentioned above. In literature we can find several definitions of the concept of start-up. For instance, a start-up can be identified as "a small company exploring new business opportunities, working to solve a problem where the solution is not well known and the market is highly volatile" (Giardino et al., 2014). However, some academics adopted shorter definitions, classifying start-ups as innovation providers with a maximum age requirement of six years old (Brush and Vanderwerf 1992; Kearney and Lichtenstein, 2022). As we can see, most definitions consider start-ups' qualitative characteristics when defining them. Therefore, we provide a qualitative definition in this work too: Blank and Dorf (2012) define start-ups as "a temporary organization looking for a scalable, repeatable, and profitable business model." Now that a definition of start-up has been provided, the next paragraphs deep dive into an analysis of the literature on scale-ups and a pre-scale-ups.

2.3.5. Qualitative scale-up definition

The first remarkable definition of scale-up is provided by Onetti (2014) that defines scale-ups as: “a development-stage business, specific to high technology markets, that is looking to grow in terms of market access, revenues and number of employees, adding value by identifying and realizing win-win opportunities for collaboration with established companies”. The article continues by defining the achieved stage of scale-up with the validation of the business model hypothesis and by overcoming the so called “growth chasm” (Moore, 2014). Even though the definition seems hazy and qualitative without the explanation of any metrics, it helps us get a taste of the scale-up concept. As this definition implies, the stage of scale-up should be achieved once a firm has already validated its business model, thus it should have already demonstrated some traction in the market. Indeed, in order to scale up its business, a company should have already proven a successful business model in which the market has shown some interest in the start-up's value proposition and the company has developed a viable way to offer its product/service. Moreover, the author suggests that the scale-up stage is specific of high-tech markets. High tech sectors can be defined as industries that present a high share of employees coming from STEM fields, namely with a scientific, technological, engineering and mathematical background (Hathaway, 2013). However, a specific meaning of the term "scaling" is not given in literature. For the sake of understanding this chapter, we can suppose that a scaling phenomenon occurs when a start-up exponentially raises its growth rate (e.g., growth in terms of sales) without significantly increasing its resources (Amaral et al., 1997; Coad, 2008; Bocken et al., 2016). Indeed, successful high-tech start-ups grow more quickly in their initial years, implying that industries with a high percentage of STEM graduates may favor business growth (Hathaway, 2013). As we can see, rather than offering meaningful metrics when discussing scale-ups, scholars typically focused on a qualitative definition of the term. However, when metrics are applied, they frequently take into account ideas like funding, growth in terms of sales and employees, and age.

2.3.6. Metrics for the scaling

Funding

A key distinction between start-ups and scale-ups based on qualitative and quantitative metrics is highlighted in the work of Cavallo et al. (2019). According to the authors, scale-ups show significant customer traction and receive funding through a first Series A round of more than $1 million. However, there are industries that are more capital-intensive, while others require less funds and allow firms to proceed through the scaling phase without the need for a series A investment round. Instead, according to Tzabbar and Margolis (2017) a venture can be regarded as being in a growth stage when it builds an innovative portfolio and receives outside funding. Therefore, the amount of capital injection necessary to take the firm's growth stage into account is not specified by the authors, and this qualitative assessment without metrics is a constant attitude of scholars in all scaling-related literature.

Patents

By contrast, the number of patents might serve as a substitute for funding if the company was unable to attract at least one outside investor. So, we can identify a business in the growth stage if it has at least one patent (Tzabbar and Margolis, 2017).

Age

Autio (2016) contends that a definition that takes traction and funding into account is still incomplete because it ignores the problem of novelty. The definition he suggests is as follows: "a scaleup is a new, entrepreneurial firm, up to 10 years old, that is strongly growth-oriented and has attracted \$1 mln or more of venture capital funding". Even though there is still a qualitative measure, namely the "growth oriented" characteristic, this definition nonetheless represents a step closer to a comprehensive definition of scale-ups. Furthermore, the time needed to reach the stage of scaling can be severely affected by the industry in which the company operates, since the growth of a business is industry-dependent (Jorgenson and Stiroh, 2000). However, a 10-year constraint could be an upper bound that encompasses the scaling stage of the majority of businesses.

Traction

A company has "traction" when there is consistently rising demand for its product or service or when customers are becoming more interested in it (Cavallo et al., 2019). So, the traction can be intended as the demonstrated interest of customers towards the value proposition of a start-up. Unfortunately, the amount of traction needed for a business to grow successfully depends on the industry that it operates in as well as the age. However, we can use the increase in sales as a proxy for the amount of market traction that a scale-up can achieve since the demonstration of interest can be quantified by the number of products/services the firm sells.

Growth and Gazelles

Holzl (2014) attempts to define the term "high growth firms" (HGF) by offering two definitions that could be used. The first definition focuses on choosing the top 1% or 5% of businesses in a sector with the fastest growth rate without defining the growth metrics that should be applied in this selection. The second, which is more thorough, defines HGFs as businesses that experienced annual sales growth of at least 50% over a 3-year period. Indeed, the sales growth represents one of the most important metrics to understand the stage of a start-up (Hashai and Zahra, 2022). However, someone can argue that a HGF can belong to both pre-scaling and scaling stage. On one hand, the 50% might be the lower bound for the pre-scaling stage. On the other hand, the HGF can be seen as a venture that is already scaling up its operations. The second scenario seems more realistic since a 50% increase represents a significant growth that is typical of a business that is already scaling up. Furthermore, this type of high growth is typical of another subgroup of scale-ups that is presented in this paragraph. So, is reasonable to assume that in literature the notion HGF is used as a synonym of scale-ups. Another possible metrics considers a venture as a HGF if the employment growth expected in 5 years is higher than average number of employees in firms that are in the same industry and country (Albert and Caggese, 2021). There is another stream of literature that tackles the concept of HGFs by referring to them as “gazelles”. Gazelles are an example of a subgroup of scale-ups that have some particular characteristics that sometimes in literature are used as a synonym of the notion of scale-up. The Organization for Economic Cooperation and Development (OECD) and Duruflé et al. (2017) define gazelles as successful scale-ups that achieved at least 20% sales and employment growth rate each year over a period of 3 years. The growth in this case takes into consideration just the turnover and employment, while we know that the “high growth” definition can be severely affected by the metrics used and its relevance can be impacted by the industry selected (Jorgenson and Stiroh, 2000; Delmar et al., 2003; Gilbert et al., 2006). Furthermore, the work of Henrekson and Johansson (2010) finds out that gazelles tend to be younger on average than common ventures. For this reason, an alternative definition of gazelles could be by adding a minimum number of 10 employees (Ahmad, 2006) and a possible maximum age of 5 years old (Duruflé et al., 2017). This type of scale-ups is essential for the development of an industry. Indeed, the increase of gazelles in an industry has a positive effect on the subsequent growth of a sector (Bos and Stam, 2014). Leaving the concept of gazelles, Tzabbar and Margolis (2017) propose a 10% growth in number of employees to consider the venture in the growth stage. However, considering just the number of employees as growth metrics for the definition of scaling can lead to severe biases since start-ups usually do not have employees when they start. While the ones that have them, are usually much bigger (Coad et al., 2020). Regarding the academic world, Huynh et al. (2017) studied the concept of academic spin-offs and their growth by relying on financial performance indicators such as growth in terms of sales revenue and net profit margin.

Valuation and unicorns

The unicorns are another intriguing ventures' subgroup. The term was first used by TechCrunch in 2013 and is now used for scale-ups that are extremely successful, similarly to the concept of gazelles discussed before. However, this subgroup has another distinctive characteristic: unicorns are successful scale-ups with valuations exceeding $1 billion, thus representing an even more exclusive club of scale-ups compared to gazelles (Autio, 2016). For sake of completeness, there is even a more elitist club that is the one formed by decacorns, namely scale-ups with a valuation of at least $10 billion (Frier and Newcomer, 2015). According to the definition of unicorns, researchers like Piaskowska et al. (2021) examined the scaling strategies of scale-ups. They employed an algorithm that allowed them to calculate a scaleup valuation for each. The scale-up's financial stability, market traction, and market size are the metrics the algorithm uses, and they are qualitatively described along their work. Then, the authors abandoned the idea of adopting a pool made up only by unicorns in order to include companies with a valuation greater than $500 million. In general, the valuation is used in order to overcome the limitations regarding the growth metrics of sales and employees (Shepherd and Wiklund, 2009). The lack of public data in entrepreneurial ventures and the aleatory behind the growth metrics in the context of young companies can prevent the proper assessment of the stage of a venture. Thus, scholars have recently begun to use company valuation, which is obtained through funding rounds, as a proxy for growth (Malyy et al., 2021).

As we can see, the definition of the concept of scale-up and the metrics that identify its boundaries appear to be scattered throughout the literature. In Table 2.1, we summed up all the scaling phase boundaries that we presented, concentrating much more on the lower ones, since our work evaluates ventures in the pre-scaling phase (i.e., the phase before). We take into account all the metrics that define scale-ups, HGF, gazelles, and unicorns together since there are no exact metrics for the stage of scale-up yet. In this way, we can see all the metrics together and assess the boundaries, being aware that there are substantial differences among the entities that we mentioned before.

Table 2.1: Summary of scaling phase boundaries

Variable	Boundary	Used by
Funding	> $1 mln (series A)	Cavallo et al. (2019)
	At least an external investor	Tzabbar and Margolis (2017)
Patents	At least one patent	Tzabbar and Margolis (2017)
Age	<10 years	Autio (2016)
	<5 years	Duruflé et al. (2017)
Traction	/	Cavallo et al. (2019)
Sales growth	>50% growth rate for 3 years	Holzl (2014)
	>20% growth rate for 3 years	OECD, Duruflé et al. (2017)
Employment growth	>20% growth rate for 3 years	OECD, Duruflé et al. (2017)
	>20% growth rate for 3 years (with 10 min)	Ahmad (2006)
	>10% growth rate	Tzabbar and Margolis (2017)
	in 5 years > avg employees	Albert and Caggese (2021)
Valuation	$500 mln	Piaskowska et al. (2021)
	$1 bln	Autio (2016)
	$10 bln	Frier and Newcomer (2015)

This Table demonstrates how scholars disagree on both the definition of scale-up and the metrics that characterize this phase of a venture's life cycle. In addition to this idea, we realized that the pre-scaling phase is not defined in the literature by any scholar.

2.3.7. The pre-scaling stage

As we can see from the analysis of the literature, scholars rarely provide a unique set of metrics to define start-ups in scaling phase. This attitude is exacerbated when considering the previous stage of the life cycle of a venture: the **pre-scaling phase**. Recalling Picken's (2017) life cycle, it appears that the notion of pre-scale-up should match the definition of a venture's transition phase proposed by the author. The scholar defines this phase with a period between 18 and 36 months. So, after these 18-36 months the venture should enter in the scaling phase. This stage is a critical period for the venture since it needs to collect all the necessary resources for the incoming scaling process, and it should begin once the start-up gained some traction in the market. For the same reasoning done before, the traction can be seen through the lenses of the growth in sales. So, the pre-scaling companies should have already demonstrated the interest of a customer segment through the sale of products/services or, at the very least, they have already created a prototype or Minimum Viable Product (MVP) to gauge client interest (Eisenmann et al., 2012). In this way we can assume that the entrepreneur has already validated or is validating the business model (or at least part of it). This development could mark a significant turning point in separating start-ups with untested ideas that have not yet encountered the market from those that have. Beside this indicator, the amount of funds is another metric that could express the engagement that pre-scale-ups create among stakeholders that believe in its success. Indeed, a possible difference between pre-scale-ups and start-ups is the attraction of some external capital. For instance, by considering a division of investment rounds composed by pre-seed, seed, round A, round B and later stages (Reiff, 2022), a pre-scale-up should have already gone through a seed stage. Indeed, a venture in pre-scaling could have collected capital through grants, crowdfunding or business angels. In this way, the external investors demonstrate the trust in the business which places the venture at a further stage compared to newly born companies. However, some businesses could reach the pre-scaling phase without the need of external investors but just relying on bootstrapping (Winborg and Landström, 2001). Thus, a broad view of the stage of pre-scaling could demand a certain amount of capital without designating its source, which could be internal or external. Lastly, there is no constraint in the literature regarding the age of firms in the pre-scaling stage. Perhaps, as was previously stated, the development of a business model firmly depends on the industry, which makes it difficult to define an age restriction transversal to all industries.

To conduct our analysis, we selected 151 start-ups in the pre-scaling stage which are trying to achieve the scale-up phase by collecting funds and resources for their rapid growth. However, only a small percentage of these start-ups will be able to scale-up their businesses successfully due to their capacity to raise financing and develop a scalable business model, knowing that coming from high-tech industries can help with this transition (Jorgenson and Stiroh, 2000; Hathaway, 2013). Furthermore, this may be dependent on the entrepreneurial teams' ambition, since the competencies held may only result in high growth if there is a desire to expand the firm (Wiklund and Shepherd, 2003). Thus, start-ups were selected by checking their legal status and growth through the database AIDA, whether they had already developed a prototype or an MVP, and whether they were innovative start-ups in search of funds through the database of the Camera di Commercio.

3 Theoretical Framework

3.1. Literature Gap and Research Question

The following section outlines our research question and suggests a possible gap in the corpus of knowledge already available on investments in human capital. This investigation resulted in the formulation of our three hypotheses, which will be discussed in detail in this chapter. As stated previously, human capital – especially when it is specific and relates to the knowledge that can be directly applied in a newly formed start-up - and common ground among team members are essential for a start-up to grow and scale (Eisenhardt and Schoonhoven, 1990; Colombo et al., 2004; Picken, 2017).

Traditionally, scholars have thoroughly examined the concepts of human capital and common ground with a focus on either some of their unique characteristics or their theoretical formalization (Schultz, 1961; Clark, 1996). More recently, these two notions have been applied to the entrepreneurial context as separate concepts, as we have observed, for instance, in the works of Unger et al. (2011) and Zheng et al. (2016). Academics, however, rarely discussed these two components together in the context of newly born companies, and the moderating effects of human capital on other relationships of interest have only been studied in a few research (Marvel et al., 2016).

There are a variety of reasons why academics are cautious to apply these concepts together to the field of entrepreneurship. First of all, it should be remembered that the start-up phenomenon is still relatively new, therefore scholars will likely continue to study human capital and common ground in this context in the upcoming years. Another explanation might be that scholars have rarely addressed how these notions could have distinct effects and relevance when dealing with start-ups and established businesses.

These considerations led us to decide to concentrate our study on the human capital investments made by entrepreneurs. Specifically, our aim is to investigate the relationship between entrepreneurs' human capital in a specific knowledge domain, common ground among teammates and entrepreneurs' human capital investments in that domain. In light of this objective, we would like to answer the following research question:

How do entrepreneurs' human capital and common ground affect the human capital investments made within a start-up?

The fundamental idea of this dissertation is to connect two distinct levels: the individual level and the entrepreneurial founding team level. Indeed, this work aims to describe the decision of the entrepreneur to invest in human capital as influenced by both individual and start-up team's characteristics. Therefore, we focus on the entrepreneur's decision to invest based on his prior knowledge and moderate this relationship with team features, namely team members' competencies and previous shared professional experiences.

3.2. Human Capital Investments: Costs and Returns

Any specific knowledge is likely to have a diminishing shelf-life in the face of continuously changing environments (Reuber and Fisher, 1999). Some skills and information will have to be unlearned or replaced with newer and better knowledge and skills. Thus, company's commitment, effort and capacity to learn quickly and continually are likely to become critical in maintaining a competitive advantage. This emphasizes the significance of investing in human capital while carefully assessing the costs and returns involved.

The expected returns on human capital investments include both the private benefits engendered by the skills and knowledge acquired by the entrepreneur through these investments and the positive effects that these skills and knowledge likely have on the entrepreneur's venture's activities. These expected returns must be greater than the entrepreneur's investment costs, otherwise the entrepreneur will not pursue the investment in human capital. Investment costs include both direct expenses incurred by the entrepreneur to develop new skills and knowledge (e.g., the fee for the education program attended if new skills and knowledge are acquired through formal education) and opportunity costs associated with the entrepreneur devoting time to skills/knowledge acquisition rather than working in his venture.

To sum up, a human capital investment is done only if:

$$Expected\ returns\ >\ Investment\ cost$$

Where:

$$Expected\ returns\ =\ Private\ benefits\ +\ Positive\ effects\ on\ the\ venture$$

$$Investment\ costs\ =\ Direct\ expenses\ +\ Opportunity\ costs$$

As a result, we can identify a relationship between the entrepreneur's private benefits (i.e., the expected returns of the investment) from human capital investments and the knowledge he already possesses in a specific knowledge domain (see Figure 3.2): as his knowledge in a specific knowledge domain increases, the expected returns on his human capital investment decrease at an increasing rate. Indeed, when the entrepreneur has scarce knowledge, a human capital investment in the domain will benefit him far more than when he has abundant knowledge. Following the same logic, the entrepreneur's opportunity cost, and thus investment costs, decrease at a decreasing rate as domain knowledge increases (see Figure 3.1). Indeed, knowledge acquisition in a known domain appears to take less time than knowledge acquisition in an unknown domain. However, the benefits of knowledge acquisition are less than proportional to the amount of knowledge possessed, which explains the decreasing rate.

To elaborate on the aforementioned idea, literature claims that newly acquired knowledge is easier to absorb when it is similar to prior knowledge. Cohen and Levinthal (1990) argue that the ability to assimilate and utilize outside knowledge, referred to as "absorptive capacity", depends on the level of prior related knowledge. Learning is a cumulative process that is facilitated when the object of learning is connected to what is already known. As a result, learning in new domains is more challenging, and an individual's knowledge about a topic changes only incrementally. Moreover, accumulated prior knowledge enhances the ability to retain new information, recall it, and apply it in new contexts (Cohen and Levinthal, 1990); psychologists suggest that prior knowledge helps learning because memory is built by associative learning, which implies that experiences are stored in it by forming links with pre-existing notions (Cohen and Levinthal, 1990). Besides, a lack of knowledge in a domain may prevent an individual or company from obtaining later expertise in that domain. In such instances, effective information acquisition may be impossible without the support of others who can "translate" the knowledge into a form that they can grasp (Reagans & McEvily, 2003).

Figure 3.1: Returns to investment curve

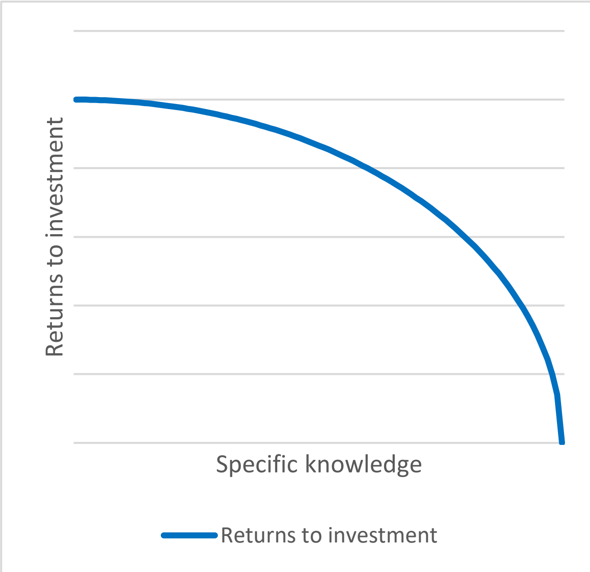
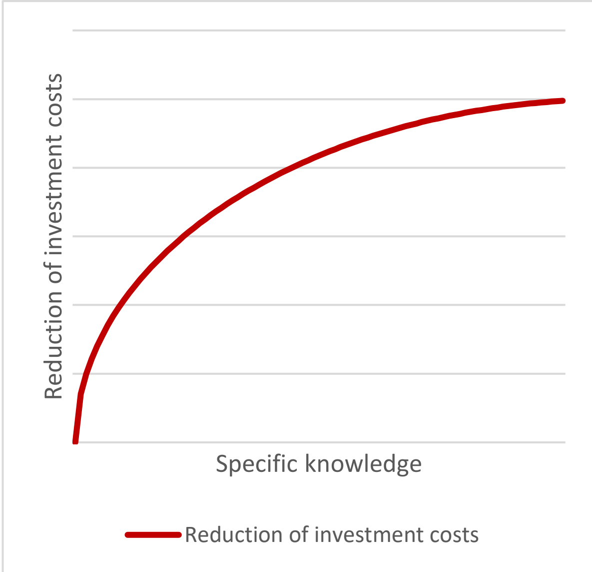


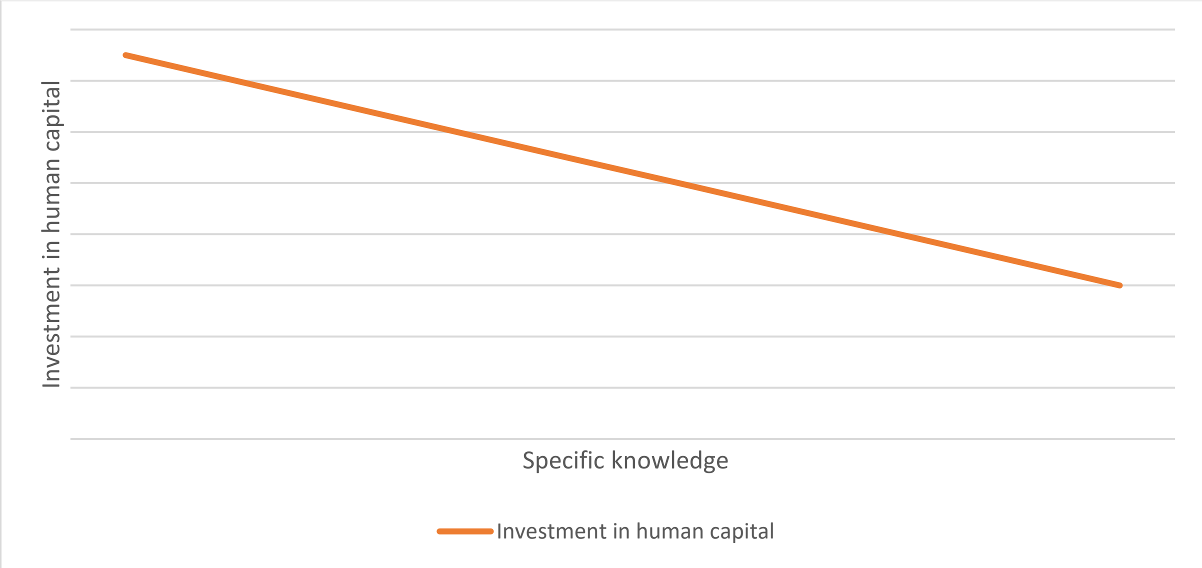
Figure 3.2: Reduction of investment costs curve



3.3. Effect of the entrepreneur's current competences on human capital investments

As previously discussed, the choice of investing in human capital is governed by the returns that this investment generates at start-up and individual's level. The returns of a human capital investment made in a specific knowledge domain decrease at an increasing rate, since as people's prior knowledge of the investment's topic rises, they receive less benefit from it. Therefore, we can assume that the level of investment in human capital strictly depends on the return trend. Indeed, as the specific knowledge of the entrepreneur in that domain increases, he will benefit less from the investment and therefore will be less keen on facing it (see Figure 3.3).

Figure 3.3: Trend of investment in human capital



Hypothesis 1 (H1): *There is a negative linear relationship between the human capital investments of an entrepreneur in a specific knowledge domain and the knowledge the entrepreneur already possesses in the domain.*

3.4. Effect of competences of team mates on human capital investments

We will now focus on the same relationship addressed in the previous hypothesis while taking into account the effect of team members' competencies. We will examine how the competencies of peers affect the expected positive returns on human capital investments made by entrepreneurs. We anticipate that by taking this new component into account, the original relationship will be strengthened or weakened. We will now focus on two main cases.

When teammates already have some competences in the domain, the expected positive effects on the venture are somehow lower than those predicted without considering team members' competencies. Indeed, the entrepreneurial team does not have a complete knowledge gap to be filled. However, acquiring some competences in this domain would allow the entrepreneur to better interact with his teammates, act more quickly, and create synergies for the venture, even if there is no knowledge gap to be filled (Zheng at al., 2016). That is the previously mentioned concept of common ground. Human capital investment may benefit a company not by filling a knowledge gap, but by establishing new common ground among team members.

When teammates, instead, have no competences in the domain, the expected positive effects on the venture are the highest since there is a significant knowledge gap to be addressed, and the investment in human capital will at least partially fill it.

As the entrepreneur's knowledge grows, the positive effects on the venture decrease in all two cases described so far, and they become negligible when the entrepreneur is an expert in the knowledge domain under consideration.

Intuitively, if we consider an entrepreneur who works in a start-up whose team lacks expertise in the given knowledge domain, we can predict that he will invest significantly more in human capital as his specific expertise decreases, compared to an entrepreneur that has a team formed by knowledgeable individuals. Indeed, the fact that teammates lack expertise in the domain strengthens the impact of the entrepreneur's prior knowledge in that domain on the degree of human capital investments. We believe that a lack of specific human capital in that domain may spur the entrepreneur to devote more time to expanding his competencies, being aware that his teammates lack expertise as well. Instead, while working with a knowledgeable team, the entrepreneur will feel less of a responsibility to invest due to his perception that some of his team members have, at least partially, covered the knowledge domain under consideration. And as a result, the knowledge-investment relationship is weakened.

For a graphical representation of these concepts, see Figures 3.4 and 3.5.

Figure 3.4: Effect of teammates' competencies on human capital investments

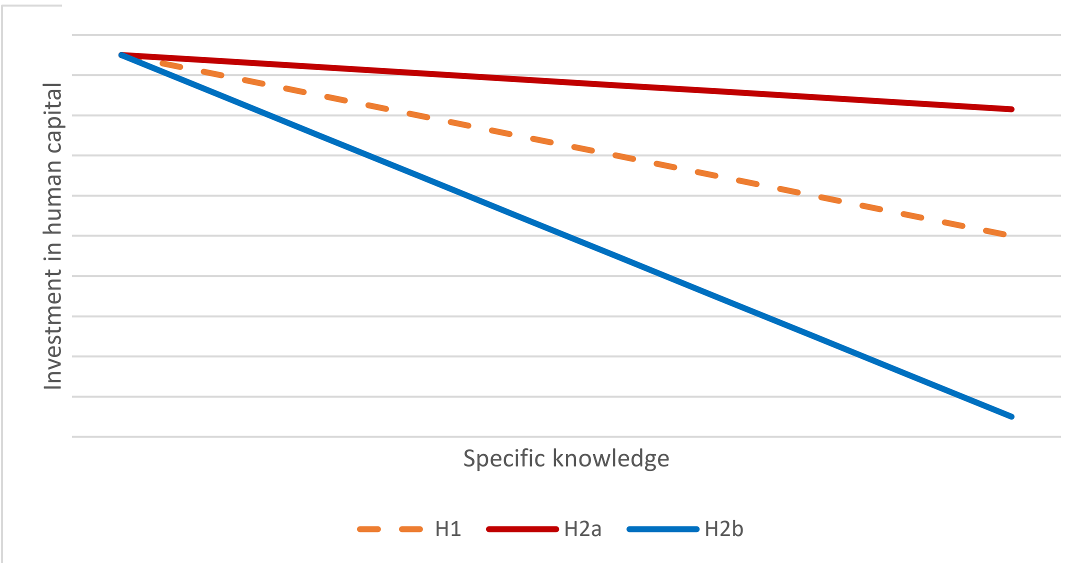
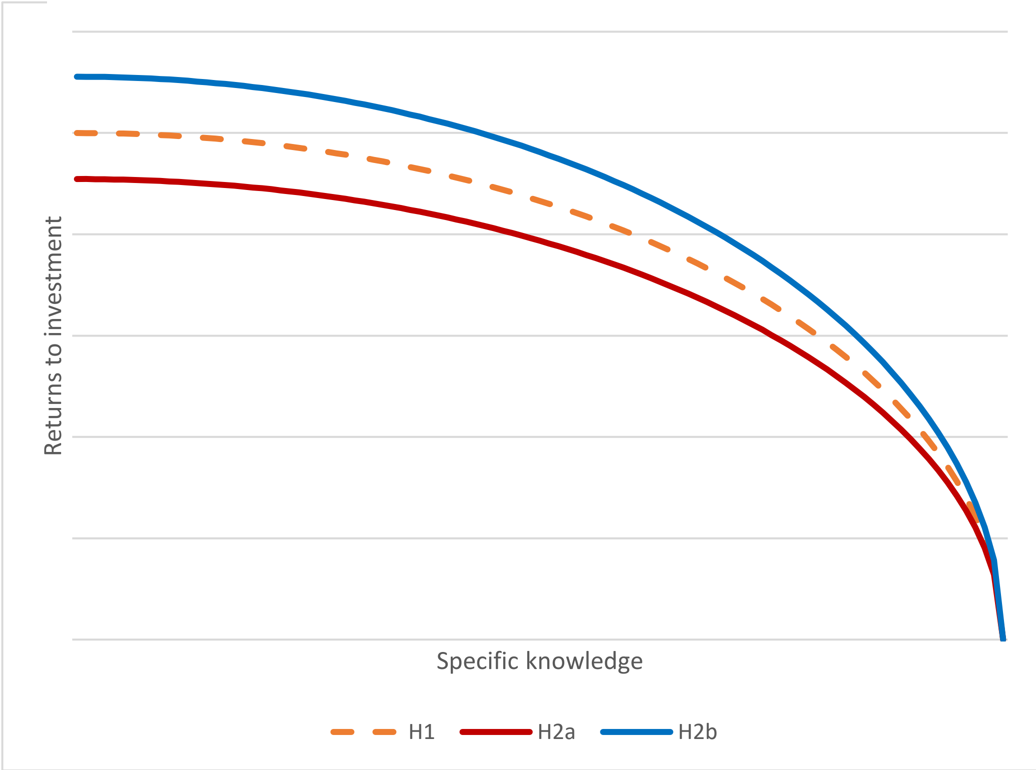


Figure 3.5: Effect of teammates' competencies on returns to investment



Hypothesis 2a: *The negative linear relationship between the human capital investments of an entrepreneur in a specific knowledge domain and the knowledge the entrepreneur already possesses in the domain flattens when the entrepreneur's teammates have already competences in the domain.*

Hypothesis 2b: *The negative linear relationship between the human capital investments of an entrepreneur in a specific knowledge domain and the knowledge the entrepreneur already possesses in the domain steepens when the entrepreneur's teammates do not have competences in the domain.*

3.5. Effect of common ground of teammates on human capital investments

In general, once an entrepreneur has acquired skills and knowledge through human capital investments, he must implement them at the team level. The presence of common ground among team members facilitates the transfer of these knowledge and skills to peers, thus making it easier to leverage them inside the start-up. Indeed, in the presence of common ground, the knowledge provider can adapt his response to what the knowledge seeker knows and does not know, boosting the response's effectiveness (Hwang et al., 2015). Instead, a lack of common ground can hinder this process, and misunderstandings are frequent (Hwang et al., 2015).

As a result, we argue that team members' common ground can play a role in altering the relationship between entrepreneurs' specific previous knowledge in a domain and their investment in human capital in that specific domain.

On the one hand, entrepreneurs with higher specific knowledge are likely to be familiar with some of the training program's contents; consequently, they will suffer a smaller opportunity cost thanks to their greater absorptive capacity. As previously stated, absorptive capacity increases with higher prior related knowledge (Cohen and Levinthal, 1990). Indeed, more knowledgeable people can absorb training content faster since they already have the theoretical framework to assimilate this new knowledge. On the other hand, people with low specific education will face higher opportunity costs, since they may require longer to comprehend and assimilate all of the concepts learned during training.

Considering that start-up members want to reduce the opportunity costs associated with human capital investments, the most cost-effective option is for experienced team members to attend the course and then share what they learn with their colleagues. Indeed, it would be meaningless at start-up level to send another team member who lacks the basis to follow the training. More experienced members can obtain new information at a lower cost, and then exploit the common ground to successfully transfer it to less knowledgeable colleagues.

As a result, we anticipate that the likelihood of attending the training will increase as the entrepreneur's specific skills grow when there is common ground among team members. When the returns from human capital investments are larger at start-up level (i.e., when the start-up has a knowledge gap), the presence of common ground will have a greater beneficial influence on the venture, whereas the effect will be minimal when the investments' gains for the venture are small.

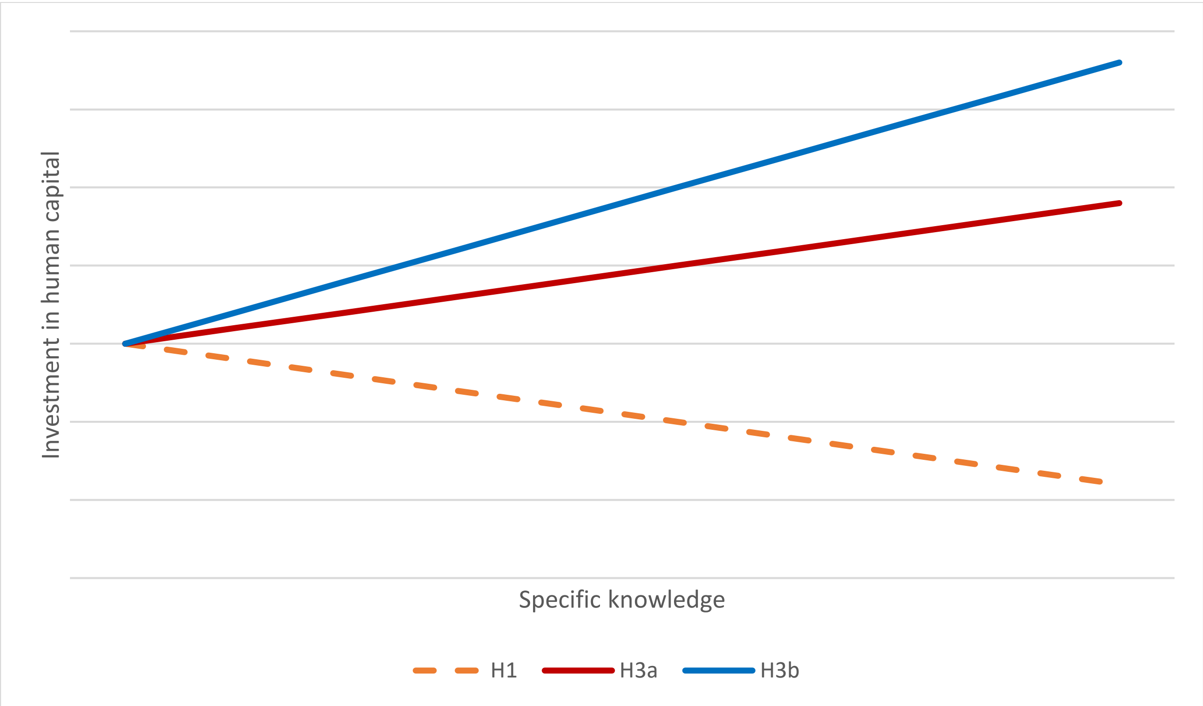
As a result, we expect that the effect of common ground will be lower in the previously described case of hypothesis 2a (i.e., team members already have some competences in the knowledge domain where the entrepreneur is investing in human capital) than in the case of hypothesis 2b (i.e., when no team members have expertise in the knowledge domain).

For a graphical representation of these concepts, see Figure 3.6.

Hypothesis 3a: *The linear relationship between the human capital investments of an entrepreneur in a specific knowledge domain and the knowledge the entrepreneur already possesses in this domain becomes positive when the entrepreneur's teammates already have competences in the domain and share common ground.*

Hypothesis 3b: *The linear relationship between the human capital investments of an entrepreneur in a specific knowledge domain and the knowledge the entrepreneur already possesses in this domain becomes even more positive when the entrepreneur's team mates do not have competences in the domain and share common ground.*

Figure 3.6: Effect of common ground on investment in human capital



4 Methodology

4.1. Research Design

We joined the InnoVentureLab team to assist with the planning and deployment of a Randomized Control Trial that involved 151 Italian start-ups, which constitute a statistically relevant sample.

InnoVentureLab is a free online pre-acceleration programme that aims to transfer methodologies and resources to assist start-ups in the development of their business model. It is sponsored by three renowned Italian universities: Politecnico di Milano, Politecnico di Torino and Centro ICRIOS of Bocconi University.

To conduct the experiment, InnoVentureLab provided a training course to a selected group of ventures in the pre-scaling phase. The course was structured into four online sessions, with the goal of transferring methodologies for financial resource management and the attraction of investors through focused activities and class discussions. To promote start-up involvement, entrepreneurs were also invited to a final "Demo Day", where they would have the opportunity to present their idea to an audience of venture capitalists and business angels. Furthermore, InnoVentureLab offered the chance to participate in webinars, workshops and monthly bootcamps related to the start-up industry for a year following the program completion.

The programme targeted a specific type of start-ups, namely those in pre-scaling phase, belonging to whatever industry. As a result, only start-ups that had validated their business idea and were building a financial strategy to sustain growth while seeking external investors were accepted. We selected these firms because they are neither established start-ups with a lot of experience that may influence the experiment, nor individuals who are simply considering becoming entrepreneurs and thus more likely to drop out due to a lack of commitment. The training was free to ensure the participation of start-ups with little financial resources.

4.2. Randomized Control Trial

As previously mentioned, the InnoVentureLab research team designed and performed a Randomized Control Trial (RCT). In the last century, randomised trials have revolutionised medicine (Duflo and Kremer, 2003) and are still commonly used in clinical research to examine the effectiveness of novel medications and assess their side effects. Moreover, as they represent the gold standard to infer cause-and-effect relationships, this kind of experiments may be particularly beneficial for testing and expanding theory in the entrepreneurial setting—an extreme organisational context characterised by uncertainty, high failure rates, and significant levels of stress and dynamism (Stevenson et al., 2020).

Randomized control trials (RCTs) are scientific experiments meant to assess the impact of different treatments by randomly allocating participants (also known as subjects) to various treatment conditions (Luca and Bazerman, 2021).

Randomized trials attempt to answer the following questions: how would individuals who received the treatment perform in the absence of it? How would individuals who were not exposed to it fare in its presence? We would like to determine the average effect of the program on a group of individuals by comparing them to a similar group of people who were not exposed to it. Indeed, comparing the same individual across time would not provide a fair estimate of the treatment's impact because numerous other factors might have changed at the same time (Duflo and Kremer, 2003).

Participants in field experiments may vary from one another owing to pre-existing differences (the so-called “selection bias”), which may severely impact the outcome of the research analysis. An RCT allows statistical control over these uncontrollable factors by randomly assigning participants among compared treatments, such that any variation in experiment results may be clearly traced to the program (Duflo and Kremer, 2003).

Not only should study participants be kept unaware of group assignment, but so should researchers, data analysts, and evaluators, so that they are not impacted by that information (Day & Altman, 2000). This technique is known as **blinding**, and it is used to minimise biased outcomes that may occur since expectation is likely to impact findings (Day & Altman, 2000).

In Table 4.1, the main terms associated with RCTs are defined (Luca and Bazerman, 2021).

Table 4.1: Key terms related to RCTs

Concept	Definition
Experiment	It is a research approach that uses randomization to investigate the causal effects of one or more input variables on an outcome variable. To be categorised as an experiment, random assignment must be present, either through the researcher's deliberate intervention or through natural occurrences.
Control group	This group acts as a comparison group for the treatment group.
Treatment group(s)	There might be more than one. The experimental individuals in these groups will get an additional treatment than the control group. Researchers alter a variable that is considered significant in one of the two groups; the remaining variables are monitored to prevent the results from being distorted by alternative explanations.
Randomization	To improve the chance of uniformity and comparability, individuals are randomly allocated to two or more groups.
Independent variable	The variable whose effect is being measured.
Dependent variable	The outcome(s) of interest.
Average treatment effect	The average effect of the treatment on the individuals being treated. This may be determined by comparing the average outcomes of the treatment groups against the control group.

Moving on to our experiment, the ultimate purpose of InnoVentureLab RCT was to determine how alternative approaches to entrepreneurial decisions impact the performance of start-ups in the pre-scale-up phase. To accomplish this, participants were randomly allocated either to a control group (n=75) or a treatment group (n=77); simple randomisation was used to avoid any imbalances between the groups. The same training course was delivered to each group in slightly different ways: control start-ups received "standard" training content, whereas treated start-ups were trained using a "scientific" approach. In order to adequately evaluate the impacts of these two different methodologies to decision making, all other factors were held constant (e.g., number of training hours, number of lessons, instructors, topics, etc.).

4.3. The training programme

Overall, the training programme was structured into four online sessions and took place between May and June 2022. Each session (for both treatment and control groups) consisted of a 2-hour lecture conducted by a trained instructor followed by a 1-hour guest session in which a successful investor or entrepreneur gave advice and coaching.

Participants were allocated to six "classes", for a total of three control groups and three treatment groups. To avoid contamination between the two groups, the training was provided on Wednesday to control groups and on Thursday to treatment groups; we also kept communication between the groups separate.

Before beginning the training, we requested start-ups to sign an agreement stating that InnoVentureLab was providing management advice and training to firms in exchange for monitoring their performance data for educational and research purposes. However, we did not advise them that there were two groups of start-ups and that the content of the training programme differed across the groups.

Instructors employed two different teaching methods depending on the nature of the group. Entrepreneurs in the treatment groups were given additional training on the theory and application of the **scientific approach** to entrepreneurial decision-making, specifically based on financial strategy themes. Treated start-ups were taught to frame, identify and validate the problem, formulate falsifiable hypotheses, test them rigorously with valid and reliable metric and set thresholds for these metrics to make decisions, as scientists do when they approach a problem (Coali et al., 2021). For further detail regarding scientific entrepreneurs' decision-making process, see Table A.1 in Appendix A.

On the other hand, entrepreneurs in the control groups were given **standard training content** based on case studies and heuristics and they were encouraged to carry out tasks using their own intuitions. As a result, control start-ups tended to keep the problem vague, neglecting to define the questions and clearly outline the decisions to be made as well as their consequences.

The duration and content of the sessions were the same for all groups in order to offer all start-ups a relevant learning experience while ensuring that the only difference in learning outcomes could be attributed to the scientific method. To eliminate potential biases caused by instructors' teaching style, each of the three teachers was assigned to both one treatment and one control group.

As shown in Table 4.2, each lecture focused on a specific topic:

Table 4.2: Structure of the training program

Lecture	Topic
Lecture 1	Definition of capital requirements
Lecture 2	Attraction of external funding; the issue of information asymmetries
Lecture 3	Choice of the funding source
Lecture 4	Potential tensions between entrepreneur and investor in the aftermath of the investment
Post training	Start-ups were motivated to participate in the data gathering process by offering them the chance to submit a pitch video that gave them access to the final "Demo Day" with investors

4.4 The Research Assistant's Role

Throughout the duration of project, we played an operational role as Research Assistants, which allowed us to collect a variety of data about the entrepreneurial teams and start-up performances in a rigorous and transparent way (see Figure A.1 in Appendix A for further information on the project's timeframe). The research assistants were specifically trained on the research protocol, how to execute interviews to collect data, and how to code and assess interview content.

Initially, we promoted the course via digital channels and reached out to entrepreneurs, accelerators, and incubators via LinkedIn and emails. We especially screened for potential applicants in the Registro Imprese database, section "Innovative start-ups currently seeking investment". The call was issued in January 2022 and was accessible until the end of March 2022; during this period, it received more than 250 applications.

Our next task was to evaluate the registered start-ups and select those who satisfied the previously specified criteria to be categorized in the pre-scaling phase. We looked for revenue figures in the AIDA database (which contains financial statements from

Italian enterprises) and we checked their websites to ensure that they had a functioning product or service, or at the very least a prototype. We also sent them a survey, asking them to self-categorize themselves across different development stages. We ended up with a final group of 151 start-ups.

During the lectures, our role was comparable to that of supervisors, providing technical and practical assistance to entrepreneurs: we accepted meeting participants and split them into rooms, gathered questions in the chat and replied to them, provided teaching material and recorded presences.

Before and after the training program, we systematically interviewed entrepreneurs to monitor the performances of their start-ups and catch changes in their business model or financial strategy. The ultimate goal was to determine which approach was the most effective (standard vs. scientific) and which strategic choices it provided (e.g., are start-ups trained with scientific method more likely to pivot their financial strategy?). We performed these online interviews because we could evaluate the extent to which the teams adopted a scientific approach to decision making only by learning about the start-ups' activities beyond the InnoVentureLab programme.

Interviews were conducted in accordance with a predefined and replicable protocol, ensuring internal validity. Each research assistant interviewed the same set of entrepreneurs over time to ensure she was familiar with their business model and financial strategy and could quickly recognise substantial changes. We also respected the universities' code of ethics, safeguarding entrepreneurs' privacy and the reliability of the data reported. The first call took place in April, and the procedure was repeated every month and a half after that. Calls lasted around 20 minutes and were recorded and transcribed so that we could listen to them again and assess them based on various factors. Overall, we collected 3 observations from April to September.

4.5 Interviews' Script and Assessment

The data gathering process consisted mainly of two activities: the creation of a pre-interview survey on Qualtrics to be submitted to the startups' founders and the execution of the rounds of interviews.

Before beginning the training program, we asked each start-up's representative (i.e., the person in charge of communicating with InnoVentureLab) to fill in a survey in order to shorten the duration of the interviews. The survey asked different types of questions, related to the following macro categories: vitae of the representative (e.g., region of origin, age, education, current occupation, previous work experience, etc.), composition of the entrepreneurial team, value proposition of the start-up, duration of previous shared experiences with other team members (during university or at work, therefore an indication of common ground). Participants gave this data with the agreement that it would be held by InnoVentureLab and not transmitted to third parties, except in anonymous and aggregate form.

Moving on to the online interviews, we asked the entrepreneurs open-ended questions and requested them to report on what they had done in the previous weeks. This way, we could judge the level of adoption of a scientific approach to decision making. Since the start-ups were unaware that they were being evaluated, the scoring reflected the interviewer's assessment. Table A.2 in Appendix A contains the script used to conduct the rounds of interviews as well as the scoring system employed to evaluate respondents' scientific approach.

4.4. Data analysis

To validate our hypotheses, we gathered participants' personal information from two different sources: start-ups' representatives were asked to fill in a survey at the time of their enrolment to InnoVentureLab, whereas information about the other team members was collected looking at their curriculum vitae posted on LinkedIn. This material was complemented with data obtained throughout the training program concerning each participant's attendance at the four online lectures.

Table 4.3 shows some descriptive statistics of the sample. The majority of start-ups in our final sample (71, or 47% of the total) are platform-based businesses, which means they provide their value proposition via a digital platform (i.e., an application); moreover, 76% of them offer a service, while the remainder sell a product. Even though they are spread across various sectors such as healthcare, food, and logistics, it is possible to notice that 18% of them offer a value proposition related to sustainability issues and circular economy solutions, in line with the fact that sustainability is a megatrend of our time that has a strong impact on businesses.

Lombardy has by far the most start-ups (32); overall, 59% of start-ups are from northern Italy, 22% from the centre, 14% from the south, and 5% from the islands. Even though Lombardy is probably overrepresented, owing to its geographic closeness to where the experiment was undertaken, this distribution between north and south is aligned with the overall distribution of economic activity in Italy (Camuffo et al., 2020).

The sample size is 355 entrepreneurs, with 81% men and 19% women. On average, the entrepreneurial founder team is composed by 3.6 members - we define an entrepreneurial founder team as a group of owners who play a key role in the venture's strategic decision making at the time of its founding (Ucbasaran et al., 2003). The average age is 39, with 7 people under the age of 25, 62 between the ages of 26 and 35, 59 between the ages of 36 and 50, and 24 above the age of 50 (this data solely applies to the ages of those who completed the survey and thereby provided us with their birth date). Most entrepreneurs (86%) work part-time in their start-up; specifically, 91% of them have another work, 6% are still students, and 2% study and work.

Regarding education, the majority of the sample (72%) has a bachelor's degree, 52% has completed a Master, whereas 27% has done MBA, and a few (10%) have a Ph.D. A large percentage of them have either engineering (25%) or economics-management (18%) backgrounds.

On average, the entrepreneurs in the sample have been working for 12 years and have 4 years of managerial experience. Unsurprisingly, half of them have launched their start-up in the same sector as the company where they previously worked; indeed, sector-specific business opportunities are more easily recognized by those who have already been employed in the target industry, as they have greater capabilities resulting from deeper knowledge of the industry (Colombo et al., 2004). Moreover, 36% of them has prior entrepreneurial experience and has previously founded one or more start-ups. It is worth investigating all of this data since the abilities of the founders are viewed as a key source of competitive advantage for new ventures (Cooper and Bruno, 1977).

Given the sample's heterogeneity, we may infer that its features adequately describe the overall Italian entrepreneurial community.

Table 4.3: Descriptive statistics of the sample

Variable	N	Mean	St. Dev.	Min	Max
Team size [#]	151	3.63	2.20	1	11
Founders' age [years]	151	39	10	20	70
Education [years]	355	3.24	2.65	0	9
Working experience [years]	355	11.81	8.94	0	51.4
Same industry working experience [years]	355	5.05	7.29	0	51.4
Managerial experience [years]	355	4.15	7.10	0	39

Regarding the values of attendance, as we can see from Table 4.4, entrepreneurs in the control group spent on average 17.5 minutes more than those in the treatment group attending the four lectures of the training program. Instead, taking the perspective of the whole start-up, control start-ups attended an average of 2.9 lectures, employing 1.2 members, whereas treated start-ups followed an average of 2.6 lectures and employed 1.1 members; moreover, 9 start-ups were always absent.

Table 4.4: Entrepreneurs' attendance in treatment and control groups

Variable	N	Mean	St. Dev.	Min	Max
Attendance (control) [min]	195	113	154.7	0	445
Attendance (treatment) [min]	206	95.5	139.5	0	445

We then built a dataset in which each entrepreneur is associated with four observations, one for each lecture of the training program. This data structure, which examines multiple subjects and how they change over time, is analogous to panel data (i.e., time-series cross-sectional data). However, panel data would necessitate sources of change across time, and over the four lectures specific human capital as well as team's common ground are fixed. As a consequence, we treat them as cross-sectional data; besides that, we adjust the fact that we are treating observations as independent even when they are not by including, on the one hand, a control for which lesson is and, on the other hand, the clustering of standard errors at the lecture level. This way, we can account for the fact that observations belong to four different moments in time related to the four lectures, thus their standard errors are correlated.

4.5. The variables of the model

4.5.1. Dependent Variable

Throughout the training programme, we maintained track of entrepreneurs' attendance at each of the four lectures and created four dummy variables, one for each training week. At the completion of the program, we combined them and created our dependent variable, named **D_Attendance**, using this information. D_Attendance is a dichotomous variable, equal to 1 if the entrepreneur attended the lecture, otherwise 0, and it is a proxy for the entrepreneur' investment in human capital. For each participant, there are four attendance records in the dataset.

4.5.2. Independent variable

Following Becker's approach (1964), we distinguish between general and specific human capital in order to build our independent variables.

In the context of our analysis, we define specific human capital as the knowledge held by the entrepreneur in a specific knowledge domain; specifically, competencies in business management and entrepreneurship are our specific knowledge, since the human capital investment relates to participation in a training program on entrepreneurial finance.

To shape entrepreneurs' specific knowledge, we build the explanatory variable **Spec_Education**, which indicates how many years the entrepreneur spent studying economics, finance, management, and entrepreneurship at the university. To measure it, we considered the minimum amount of time it takes to obtain a specific degree (Colombo et al., 2004). Regardless of the field, a bachelor's degree in Italy requires 3 years of study, whereas a Master can be obtained in 2 years; an MBA lasts 1 year, and a PhD program requires 3 years. Time spent taking training courses outside of university was not taken into consideration, since unlike academic experience, knowledge transfer is not guaranteed. Only degrees in Economics, Management, and Entrepreneurship were included in the assessment, and entrepreneurs' specific education was evaluated by adding the years based on their educational attainments.

Although we acknowledge that job experience related to financial aspects may be interesting to investigate as independent variable (as work experience enables to acquire different types of competencies compared to academic experience) we did not use it due to sample characteristics - just 16% of entrepreneurs have work experience in Finance, Administration, Planning and Control.

According to our hypotheses, there should be a linear decreasing relationship between entrepreneurs' specific knowledge and their choice to invest in human capital.

4.7.3 Control Variables

We included a set of controls based on a careful review of prior studies to improve the internal validity of our research by limiting the influence of confounding and other extraneous factors on the final outcomes.

The first group of controls is related to entrepreneur's characteristics. First, we control for sex (**D_Female**), as males are more likely to become self-employed and to succeed as such (Van der Sluis et al., 2008). Second, we control for founders' years of formal education (**Gen_Education**), to distinguish between those who have never attended university and those who have studied non-specific topics. Furthermore, we control for the entrepreneurs' employment status outside the start-up—whether he works or studies besides the entrepreneurial activity (**D_Other_Activity**).

The second group of controls, instead, is connected to start-up's characteristics, and includes the number of members in the entrepreneurial team (**Ln_Team_Size**). We control for the size of the founding team since prior research has demonstrated that it may be connected to the overall knowledge stock accessible to the team (Kor, 2003). Moreover, we log transformed this variable to account for the presence of few particularly large teams.

The third set of controls deals with general characteristics of the lectures. Specifically, we control for whether the start-up is in the treatment or control group (**D_Treatment**) to determine if there is any difference between the two groups; we control for the presence of more than one team member of the same start-up at the same lecture (**D_Others_Lecture**); we additionally control for the number of the lecture (**Module**).

For a more detailed description of these variables, see chapter 5.

4.7.4 Moderator Variables

A moderator variable is a variable that interacts with another variable in such a way
A moderator variable is a variable that interacts with another variable in such a way
that the effect of the other variable changes with the value of the moderator. We will add moderation effects to our statistical model to test hypotheses 2 and 3.

The first moderator variable takes into account team members' competencies. Specifically, we define the dummy **D_Others_SE**, which has a value of 1 when at least one of the entrepreneur's teammates has a university degree in economics, finance, management, or entrepreneurship, and a value of 0 when none of the members has studied those disciplines.

The second moderator variable shapes the common ground that binds each member to the rest of the team. People accumulate common ground when they perform a joint activity; according to Clark (1996), the common ground at any given time for most activities may be classified into three main categories: (a) initial common ground; (b) public events so far; and (c) the current state of the activity.

The **initial common ground** is the set of background information, assumptions, and beliefs that the participants presupposed when they began working together (Clark, 1996). It entails not just their common general knowledge of the world, but also all the conventions they are familiar with that are related with their specific joint activity. It also encompasses what the parties know about each other prior to the engagement, such as the others' education and training, routines, and working styles (Klein et al., 2005). Consider a chess game as an example. When two players enter a game, they each assume the rules, how to interpret the chess board, the playing etiquette, what are the most effective tactics; if they have previously played each other, they also assume something about each other's strengths, weaknesses, strategies and attitudes (Clark, 1996).

Public events so far are the events the participants presuppose have occurred in public since the beginning of their joint activity (Clark, 1996). It involves knowing the event history, namely the activities that participants have performed together up to the current state (Klein et al., 2005). The main public events in chess are the players' moves, which are reflected in a game record (Clark, 1996).

The **current state of the activity** is what the participants presuppose to be the state of the activity at the moment (Clark, 1996). The physical "scene" offered by the current state acts as a form of cumulative record of past activity, and highlights what is most crucial in the scene for future operation (Klein et al., 2005). As an example, the chess board and its pieces are an external representation of the current state (Clark, 1996).

We decided to focus our research on a broad definition of common ground; consequently, we attempted to devise a proxy for the initial common ground. Following Clark's definition, we investigated whether team members had prior shared professional experiences, even in different time periods. Thus, we assume that individuals tackle issues, approach situations and express themselves in similar manners owing to the heritage of common experiences lived in a specific context. In this sense, the simultaneous presence of the two individuals in the setting is not relevant. We looked through the entrepreneurs' LinkedIn profiles to determine if they had worked for a firm where one or more of the other members had also worked. Using this data, we built the dichotomous variable **D_Same_Firm,** which assumes value 1 if the entrepreneur has previous shared professional experiences with his teammates.

In Table 4.5, we illustrate the descriptive statistics of the variables.

Table 4.5: Descriptive statistics of variables

Variable	Obs.	Mean	Std. Dev.	Min	Max
D_Attendance	1420	.335	.472	0	1
Spec_Education	1180	1.115	1.96	0	8
Gen_Education	1180	3.247	2.651	0	9
D_Female	1412	.195	.397	0	1
D_Other_Activity	1228	.739	.439	0	1
Ln_Team_Size	1420	1.115	.603	0	2.398
D_Others_Lecture	1420	.395	.489	0	1
Module	1420	2.5	1.118	1	4
D_Treatment	1420	.538	.499	0	1
D_Others SE	1200	.393	.489	0	1
D_Same_Firm	956	.36	.48	0	1

It is worth noting that the mean value of entrepreneurs' specific education is 1.11, indicating that the vast majority of people (55%) do not have degrees in Economics, Management, or Entrepreneurship. Despite this, the sample is well-educated, with a mean of 3.25 years of general education.

The correlation matrix of the variables is shown in Table 4.6. The relationships may vary from -1 (perfect negative relationship) to +1 (perfect positive relationship), via 0 (no relationship). Correlation across variables is generally low, implying that there is no substantial problem of multicollinearity.

Table 4.6: Correlation matrix

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
(1) D_Attendance	1.000					
(2) Spec_Education	-0.032	1.000				
(3) Gen_Education	-0.074	-0.532	1.000			
(4) D_Female	0.012	-0.068	0.115	1.000		
(5) D_Other_Activity	-0.095	0.011	0.172	-0.117	1.000	
(6) Ln_Team_Size	-0.331	0.013	0.059	-0.020	0.049	1.000
(7) D_Others_Lecture	-0.207	-0.098	0.156	0.045	0.086	0.235
(8) Module	-0.110	0.000	0.000	0.000	0.000	0.000
(9) D_Treatment	-0.050	0.038	0.009	-0.042	-0.030	0.117
(10) D_Others_SE	-0.204	0.217	-0.144	-0.097	0.044	0.367
(11) D_Same_Firm	-0.010	0.011	0.168	0.049	0.136	0.014

Continues below

Continued from above

Variables	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
(1) D_Attendance					
(2) Spec_Education					
(3) Gen_Education					
(4) D_Female					
(5) D_Other_Activity					
(6) Ln_Team_Size					
(7) D_Others_Lecture	1.000				
(8) Module	-0.151	1.000			
(9) D_Treatment	-0.075	0.000	1.000		
(10) D_Others_SE	0.144	0.000	0.080	1.000	
(11) D_Same_Firm	0.059	0.000	0.075	-0.009	1.000

5 Empirical Analysis

5.1. Hypothesis 1

5.1.1. Econometric model of H1

We investigate the relationship between human capital investments and specific knowledge via econometric estimates of a model that links entrepreneur's attendance at the training program to a variable describing his specific human capital and a set of control variables.

Table 5.1 summarizes the variables used to test hypothesis 1.

Table 5.1: Description of H1 variables

Variable	Type	Description
D_ATTENDANCE	Dependent variable	Dummy variable that assumes value 1 if the entrepreneur attended the lecture, and 0 otherwise. It is a proxy of the entrepreneur's investment in human capital.
SPEC_EDUCATION [years]	Independent variable	It is the number of years that the entrepreneur spent acquiring formal education in economics, finance, management, or entrepreneurship.
D_FEMALE	Control variable	Dummy variable indicating the member's gender: 1 if female, 0 if male.
GEN_EDUCATION [years]	Control variable	It is the number of years that the entrepreneur spent acquiring formal education.
D_OTHER_ACTIVITY	Control variable	Dummy variable that assumes value 1 if the entrepreneur carries out another activity (study or work) outside the start-up, and 0 otherwise.

***LN_TEAM_SIZE** [#]*	Control variable	It is the logarithm of the absolute number of team members of the start-up.
D_TREATMENT	Control variable	Dummy variable that assumes value 1 if the start-up belongs to the treatment group and 0 if the start-up belongs to the control group.
D_OTHERS_LECTURE	Control variable	Dummy variable that assumes value 1 if the entrepreneur attended the lecture with one or more team members, and 0 otherwise.
***MODULE** [#]*	Control variable	It ranges from 1 to 4 and denotes the number of the lecture.

The basic statistical model is as follows:

$$Prob(D\_Attendance) = b_0 + b_1 Spec\_Education + \gamma Controls + \varepsilon$$

Where b_0 is the intercept (also known as constant), b_1, and γ are the regression coefficients and ε is a random error term. The dependant variable denotes the investment decision, namely the likelihood that a start-up member attends a lecture of the training program. As previously mentioned, specific knowledge (i.e., the knowledge that the entrepreneur holds in a specific domain), is shaped by the variable Spec_Education, which refers to the specific knowledge acquired by the individual through formal schooling in economics, finance, management, or entrepreneurship topics.

Our aim is to examine how the entrepreneur's choice to invest in human capital in a particular knowledge domain is influenced by the knowledge he already holds in that domain.

According to H1, we expect a negative and significant coefficient of b_1, thus providing statistical evidence of a negative linear relationship between the independent and the dependent variable.

Having a dichotomous outcome variable, we decided to run a set of *probit* regressions on Stata with robust standard errors to account for the problem of **heteroscedasticity** and obtain a more precise assessment of regression coefficients' standard error. Heteroscedasticity is common in cross-sectional data and occurs when the variance of the disturbance (error term) is not constant over the whole range of data. This increases the variance of the regression coefficient estimates, but the regression model ignores it; as a result, it raises the risk that the model may declare that a term is statistically significant when it is not.

We additionally clustered by module to account for the fact that observations belong to four different moments in time related to the four lectures, thus their standard errors are correlated.

5.1.2. Empirical results of H1

The results of the statistical models for hypothesis 1 are shown in Table 5.2.

Table 5.2: Specific education and entrepreneur's probability of attending a lecture

D_Attendance	Coef.	St. Err.	Sig
Spec_Education	-.042	.017	**
D_Others_SE	-.367	.127	***
D_Same_Firm	.213	.04	***
Gen_Education	-.075	.017	***
D_Female	-.147	.104	
D_Other_Activity	-.184	.043	***
Ln_Team_Size	-.707	.037	***
D_Others_Lecture	-.553	.293	*
Module: base 1		.	
2	-.442	.063	***
3	-.568	.062	***
4	-.51	.071	***
D_Treatment	-.148	.069	**
Constant	1.595	.16	***

*The Table lists probit regression coefficients and corresponding standard errors (in round brackets) for each explanatory variable and the constant term. The outcome variable is a dichotomous variable that assumes a value of 1 if the entrepreneur attended the lecture, and 0 otherwise. The independent variable in is Spec_Education. *** p<.01, ** p<.05, * p<.1. Number of observations= 876*

It is not possible to interpret the estimated coefficients from a probit regression's output directly; instead, one must interpret the marginal effects of the regressors, or how much the (conditional) probability of the outcome variable changes when the value of one regressor is changed while holding all other regressors constant at some values.

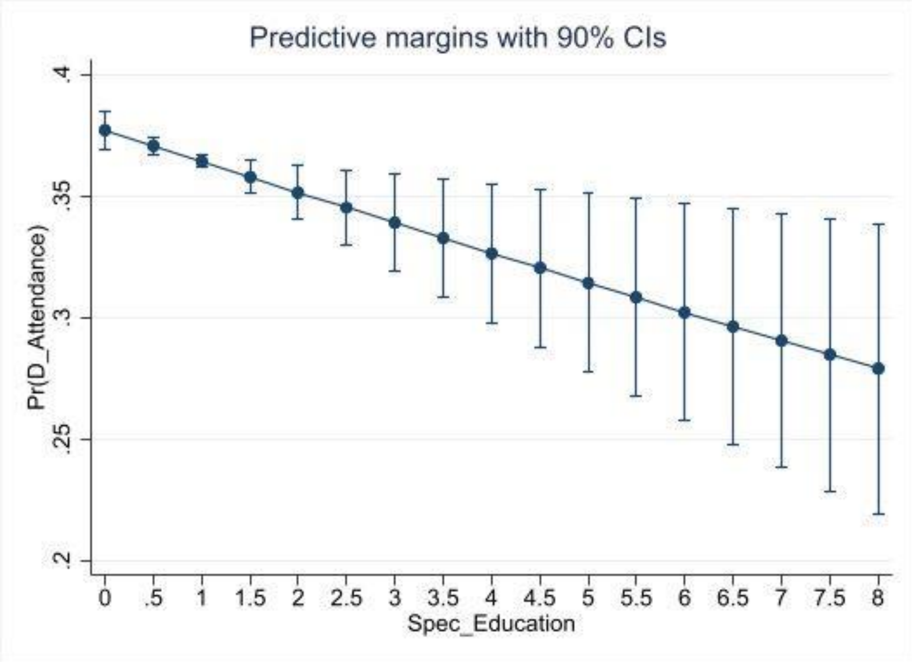
The coefficient of the constant is positive and statistically significant ($\beta=1.59$, $P<.01$). The coefficient of the independent variable is negative and significant ($\beta=-0.042$, $P=.013$), revealing the presence of a small but significant negative linear relationship between the entrepreneurs' prior education in economics and management disciplines and his investment in human capital in the same domain. As a result, **hypothesis 1 is validated**: the probability that an individual will attend a lecture diminishes as his level of expertise in the subject area in which he is acquiring new knowledge increases. Specifically, in terms of marginal effects, the likelihood of attending the lecture will drop by 1.29 percentage points if entrepreneurs' specific education increases by one year.

We argue that the main rationale for this finding is related to the returns associated with the human capital investment, which may include advantages for the start-up as well as personal advantages. If the predicted returns are not higher than the investment expenses, the entrepreneur will not proceed with the investment in human capital. Our findings clearly illustrate that adding human capital causes the investment's return to decrease.

The human capital investment yields the highest predicted returns when entrepreneurs have low levels of specific education: by acquiring new knowledge, they will be able to fill their knowledge gap on the topic and apply what they learn to their start-up's advantage. The likelihood of attendance is therefore very high. Predicted returns decline at an increasing rate as domain competence increases, lowering attendance probability. The more entrepreneurs are knowledgeable about the subject, the less advantageous it is for them to attend the course due to their prior competencies. They would be better off using their time to support the business endeavour.

This evidence is confirmed in Figure 5.1, which shows a graph that includes the predictive probability of attendance for different levels of specific education, while holding the other variables at their mean.

Figure 5.1: Predictive probability of attendance at different levels of specific education



As shown in graph, the confidence interval widens as the variable that represents the individual's prior human capital increases, reaching its maximum width when Spec_Education is at its highest value. This may occur because, due to sample characteristics, results are driven by a small number of observations: indeed, given the limited sample size, there is insufficient heterogeneity for this specific metric. This is supported by the fact that only a small proportion of individuals have high specific human capital, and for about 55% of entrepreneurs the value of Spec_Education is 0.

Moving on to the control variables, the coefficient of variables with p-values greater than the *P>0.1* threshold is not analysed since any interpretation is inaccurate owing to random variation, and there is no clear evidence that the variable has any effect at all on the outcome.

The D_Female dummy, which specifies whether the participant is male or female, is not significantly associated with the dependent variable (*P=.161)*, implying that the participant's gender has no impact on the probability to attend the training. This might be attributable to dataset features, since there is a considerable gender imbalance in the sample – females account for just 19% of the whole dataset. Indeed, a variable might be insignificant because the sample size is too small to offer proof of a significant effect, even if it exists.

The coefficient of Ln_Team_Size, which indicates the logarithm of the size of the entrepreneurial founding team, is negatively and statistically significantly associated with the dependent variable *(β=-0.707, P<.01).* In terms of marginal effects, a one unit increase in the value of the variable leads to a decrease of 21.7% in the probability that a member will be present. There are several explanations for the lower attendance with larger teams. First, based on the dataset, it is likely that most start-ups have chosen a subset of team members to engage in the training rather than the entire start-up; as a result, many members of start-ups with larger teams never attended. Second, within a large team, it is likely that someone is already familiar with the content of the training program, which may have discouraged his or her colleagues from attending. Finally, while in a small team acquiring new knowledge has an immediate impact on the whole start-up, this benefit may not be evident in a large team, deterring individuals from attending lectures.

The coefficient of Gen_Education, which reflects the general level of education of founders, is negative and significant *(β=-0.074, P<.01)*; this means that that more educated people invest less in human capital. An increase in one year in the variable leads attendance probability to decrease by 2.29%. A possible explanation for this negative relationship is that start-ups may have decided to train predominantly less educated team members due to time constraints. Indeed, better educated employees have developed specific competencies that are crucial to the start-up's operation as a result of their prior investment in education; hence, their time is precious. Less educated people, on the other hand, may lack these specialized abilities, allowing them to invest their time in being trained on financial strategy topics that might benefit the start-up's growth.

The coefficient of D_Other_Activity, which indicates whether the entrepreneur studies or works outside the startup, is negative and significant *(β=-0.183, P<.01).* Talking about marginal effects, when this variable assumes the value 1, the probability that the member is present decreases by 5.74%. This is most likely associated with the fact that people with lots of commitments have less time to devote to their formation, even though it could be beneficial to their start-up.

D_Others_Lecture, which communicates whether the entrepreneur attended the lecture with some of his teammates, is negative and significant at 10% *(β=-0.553, P=.059).* When this variable assumes the value 1, the probability of attendance decreases by 17.13%. Members of the same team may have alternated throughout the lecture, or they might have disconnected earlier because they were aware that a colleague was there and might report the content of the missing lesson, which could account for this negative association.

The categorical variable Module, which denotes the number of the lecture, reveals that lectures 2, 3, and 4 have lower attendance probabilities than lecture 1 (the baseline category). A significant and positive coefficient for the dummy module 1 indicates a higher likelihood of attending the first lecture than the others; attendance is negatively impacted by the dummy modules 2, 3, and 4, which have negative and significant coefficients. Comparing lectures 2, 3, and 4 to lecture 1, the likelihood of attendance drops by 14.21%, 17.96%, and 16.27%, respectively. This might be as a result of the level of curiosity and attentiveness diminishing after each lecture.

Finally, the control variable D_Treament is negative and significant *(β=-0.147, P=.033),* possibly as a result of the more challenging training material provided to treated start-ups, which may have deterred entrepreneurs from attending. A change in the value of this dummy from 0 to 1 is associated with a 4.56% decrease in the probability of being present.

The linear term of the moderator variables, which will be used to test hypotheses 2 and 3, is also included in the model.

D_Others_SE, which displays whether or not an entrepreneur's teammates have specific expertise in the field, is negative and significant (*β=-0.367, P=.004*): when this variable takes value 1, the probability of attendance decreases by 11.38%. This may be the result of colleagues relying on someone who is already familiar with the training program's material rather than actually attending the course.

D_Same_Firm, which indicates whether the entrepreneur has previously worked with one/some of his teammates in the same company, is positively and significant associated with the probability of attending the lecture *(β=0.212, P<.01).* A change in the value of this dummy from 0 to 1 is associated with a 6.58% increase in the probability of being present. More common ground among team members may lead entrepreneurs to attend more, as they know they will be able to leverage effectively at the team level the acquired knowledge, thanks to smooth communication procedures.

5.2. Hypothesis 2

5.2.1. Econometric model of H2

To test H2, we will now introduce the second level of analysis, namely the start-up perspective.

We focus on the same relationship that was addressed in the previous hypothesis while adding the moderation effects of team members' competencies. Specifically, we want to investigate how entrepreneurs' investment in human capital is influenced by the competences of their start-up's peers in that domain; in other words, we would like to examine how being in a team of expert financial professionals versus a team of inexperienced individuals affects participation. Indeed, if there was no expert in financial topics within his or her start-up, an entrepreneur would be more inclined to attend the lectures; on the other hand, if he worked in a start-up composed of former CFOs, he would have less incentive to participate in the training program because he would be aware that his team members are already competent in the subject.

Table 5.3 illustrates the newly introduced moderator variable.

Table 5.3: Description of H2 moderator variable

VARIABLE	TYPE	DESCRIPTION
D_OTHERS_SE	Moderator variable	Dummy variable: it assumes value 1 when at least one team member has a university degree in economics, finance, management, or entrepreneurship (i.e., they have completed at least one year of specific education); it assumes value 0 when none of the team members have specific knowledge.

Accordingly, the statistical model used to test H2 is the following:

$$Prob(D\_Attendance) = b_0 + b_1 Spec\_Education + b_2 D\_Others\_SE + b_3(D\_Others\_SE * Spec\_Education) + \gamma Controls + \varepsilon$$

5.2.2. Empirical results of H2

When the interactive term is added, the results suggest that team member's competencies moderate the relationship between the knowledge hold by the entrepreneur in a knowledge domain and his investment in human capital.

The findings of the empirical analysis conducted in relation to hypothesis 2 are displayed in Table 5.4.

Table 5.4: Specific education and entrepreneur's probability of attending a lecture: effect of team members competencies

D_Attendance	Coef.	St. Err.	Sig
Spec_Education	-.087	.037	**
D_Others_SE	-.45	.106	***
Spec_Education#D_Others_SE	.076	.038	**
D_Same_Firm	.203	.043	***
Gen_Education	-.075	.017	***
D_Female	-.134	.105	
D_Other_Activity	-.194	.04	***
Ln_Team_Size	-.724	.039	***
D_Others_Lecture	-.542	.296	*
Module: base 1		.	
2	-.44	.063	***
3	-.567	.061	***
4	-.509	.07	***
D_Treatment	-.141	.069	**
Constant	1.643	.143	***

*The Table lists probit regression coefficients and corresponding robust standard errors (in round brackets) for each explanatory variable and the constant term. The outcome variable is a dichotomous variable that assumes a value of 1 if the entrepreneur attended the lecture, and 0 otherwise. The independent variable in is Spec_Education and the moderator is D_Others_SE. *** p<.01, ** p<.05, * p<.1. Number of observations= 876*

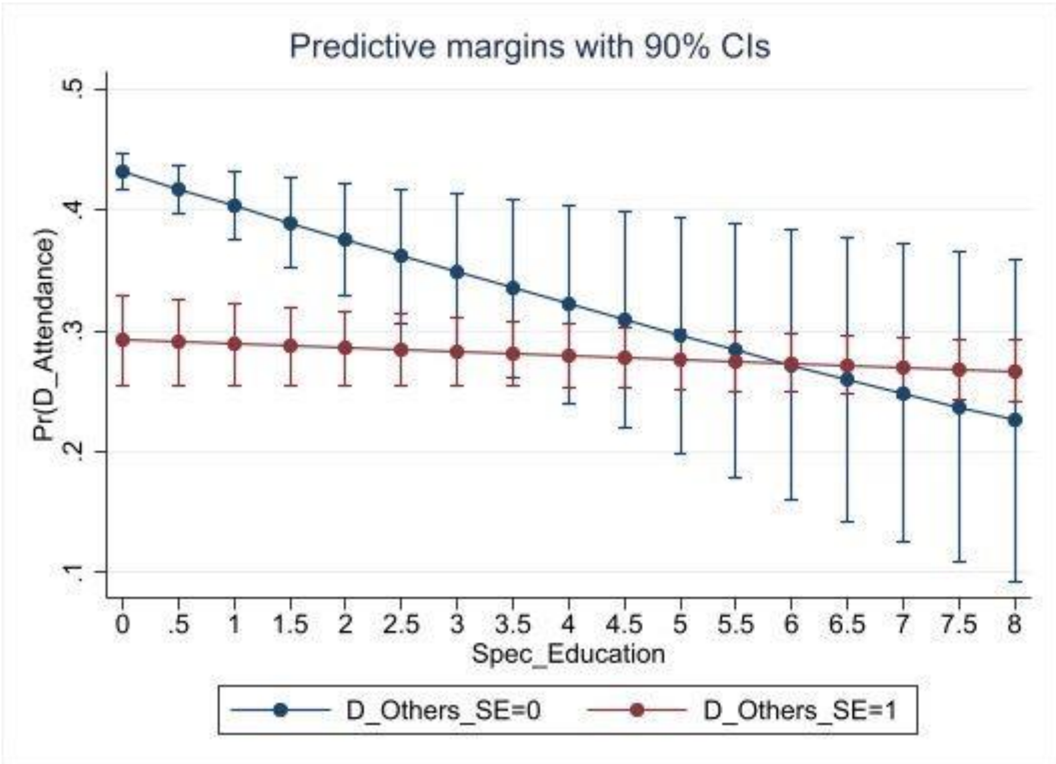
It should be taken into account for the subsequent analysis that including an interaction term in a model fundamentally alters how all the coefficients are to be interpreted. Due to interaction, the effect of having more specific education varies depending on the team members' level of expertise.

The interaction term is significant *(P=.047)*, meaning that there is a statistically significant interaction between the two factors taken into account: the competencies of the other members of the entrepreneurial founding team have a substantial influence on the outcome.

The coefficient for Spec_Education is **-0.087** (b1), which is the slope of the regression line when entrepreneur's teammates have no competencies in the specific knowledge domain (i.e., D_Others_SE =0). This coefficient is statistically significant *(P=0.020).* The magnitude of the interaction's coefficient is 0.075 (b3), which is the difference in slope between the two regression lines. Instead, when at least one of the teammates has specific competencies. (i.e., D_Others_SE =1), the slope of the line is about -0.087-0.075= **-0.012** (b1+b3). This basically means that the regression line is steeper when team members lack competencies compared to when they possess them. However, this second coefficient is not statistically significant *(P=0.238).*

To better understand the interaction effect on the original relationship, Figure 5.2 displays a graph that shows the predictive probability of attendance with respect to team members' competencies at various level of specific education.

Figure 5.2: Predictive probability of attendance with respect to team members' competencies at various levels of specific education



The moderator variable can cause an amplifying or weakening effect between the dependent and the independent variable.

When at least one of the entrepreneur's teammates has economic, managerial or entrepreneurial knowledge (i.e.., D_Others_SE=1), there is a weakening of the linear decreasing relationship between an individual's likelihood of participating in the lecture and their specific knowledge. Due to the small and negative slope value (**-0.012**), the regression line becomes almost horizontal. However, as previously highlighted, the coefficient of Spec_Education is not statistically significant. Thus, **hypothesis 2a is not validated.** The significant interaction term tells us that the slopes differ from each other but not whether each slope differs from zero (Frazier et al, 2004). Looking at Figure 5.2, we cannot tell that the slope representing the relation between attendance and specific education when teammates have competencies in the domain significantly differs from zero. As a consequence, we can state that specific education does not have an effect when D_Others_SE= 1.

The coefficient's insignificance may be related to sample characteristics. Indeed, specific education values are mainly small (mean is 1.11), implying that the majority of the entrepreneurs did not study management and economics at university. As a result, most teams will almost certainly have knowledge gaps (i.e., D_Others_SE=0). Hence, due to the small number of observations, evidence of a significant effect cannot be provided in the case of knowledgeable teammates (i.e., D_Others_SE=1).

Instead, when no one of the entrepreneur's teammates has an economic, management, or entrepreneurial degree (i.e., D_Others_SE=0), the linear decreasing relationship between an individual's specific knowledge and their likelihood of attending the course becomes stronger. Indeed, the slope of the regression line is **-0.087** and it is statistically different from zero. By comparing this regression line with the one obtained testing hypothesis 1, it is possible to see that the line gets steeper and therefore originates at higher probabilities of attendance when the moderation effect is included. Thus, **hypothesis 2b is supported**: when teammates lack management, economics, or entrepreneurial knowledge, there is a higher likelihood that the entrepreneur will invest in human capital when he has low levels of prior knowledge.

This happens because the projected positive returns on the human capital investments made by entrepreneurs are influenced by peers' competencies. Since we are focusing on entrepreneurial teams who have a substantial knowledge gap in the domain of the training program, investing in that domain will provide the highest expected returns by filling the knowledge gap of peers, at least partially. Indeed, it is very advantageous for the entrepreneur to acquire new knowledge and skills as they will benefit everyone within the start-up and facilitate the growth of the business. The beneficial effects on the business venture diminish as the entrepreneur's expertise in the domain grows and they become negligible when the entrepreneur is an expert on the subject matter, which explains the negative slope of the regression line.

By excluding the moderator variable, we would have masked the fact that the relationship is substantially stronger in teams with a knowledge gap than in teams with domain competencies.

5.3. Hypothesis 3

5.3.1. Econometric model of H3

To test hypothesis 3, we take a step forward and add another moderator variable to the previously established relationship, resulting in a three-way interaction between one continuous variable and two categorical variables. We now intend to evaluate the moderating influence of both teammates' competencies and common ground on human capital investments. Indeed, a high degree of common ground among team members enables the easy transmission of newly acquired skills and information at the team level; a lack of common ground, instead, might hinder this process. Furthermore, when the entrepreneur's competence in the domain is low, increments in common ground will have a higher beneficial effect on the venture.

Table 5.5 shows the moderator used to test the hypothesis.

Table 5.5: Description of H3 moderator variable

VARIABLE	TYPE	DESCRIPTION
D_SAME_FIRM	Moderator variable	Dummy variable that assumes value 1 if the entrepreneur has previous shared professional experiences with his teammates, and 0 otherwise.

As a result, the statistical model used to assess H3 is as follows:

$$Prob(D\_Attendance) = b_0 + b_1 Spec\_Education + b_2 D\_Team\_SE + b_3 D\_Same\_Firm + b_4(D\_Other\_SE * D\_Same\_Firm * Spec\_Education) + \gamma Controls + \varepsilon$$

5.3.2. Empirical results of H3

Table 5.6 summarizes the findings of the econometric analysis.

Table 5.6: Specific education and entrepreneur's probability of attending a lecture: effect of team members competencies and common ground

D_Attendance	Coef.	St. Err..	Sig
Spec_Education	-.137	.023	***
D_Others_SE	-.475	.065	***
Spec_Education#D_Others_SE	.121	.03	***
D_Same_Firm		.	
1	.082	.073	
Spec_Education#D_Same_Firm		.	
1	.205	.111	*
D_Same_Firm#D_Others_SE		.	
1	.064	.312	
D_Same_Firm#D_Others_SE#Spec_Education		.	
1	-.18	.099	*
Gen_Education	-.069	.016	***
D_Female	-.15	.097	
D_Other_Activity	-.186	.028	***
Ln_Team_Size	-.717	.023	***
D_Others_Lecture	-.529	.305	*
Module: base 1		.	
2	-.44	.065	***
3	-.572	.067	***
4	-.51	.073	***
D_Treatment	-.141	.069	**
Constant	1.648	.143	***

*The Table lists probit regression coefficients and corresponding robust standard errors (in round brackets) for each explanatory variable and the constant term. The outcome variable is a dichotomous variable that assumes a value of 1 if the entrepreneur attended the lecture, and 0 otherwise. The independent variable in is Spec_Education and the moderators are D_Others_SE and D_Same_Firm. *** p<.01, ** p<.05, * p<.1. Number of observations= 876*

For the sake of clarity, Table 5.7 displays the coefficients of specific education variables for all possible combinations of the values for D_Others_SE and D_Same_Firm.

Table 5.7: Role of specific education according to the moderator effect of team members' competencies and common ground

	D_Others_SE= 1 **D_Same_Firm= 0**	**D_Others_SE= 1** **D_Same_Firm= 1**
Spec_Education	-0.0160 (0.014)	0.009 (0.020)

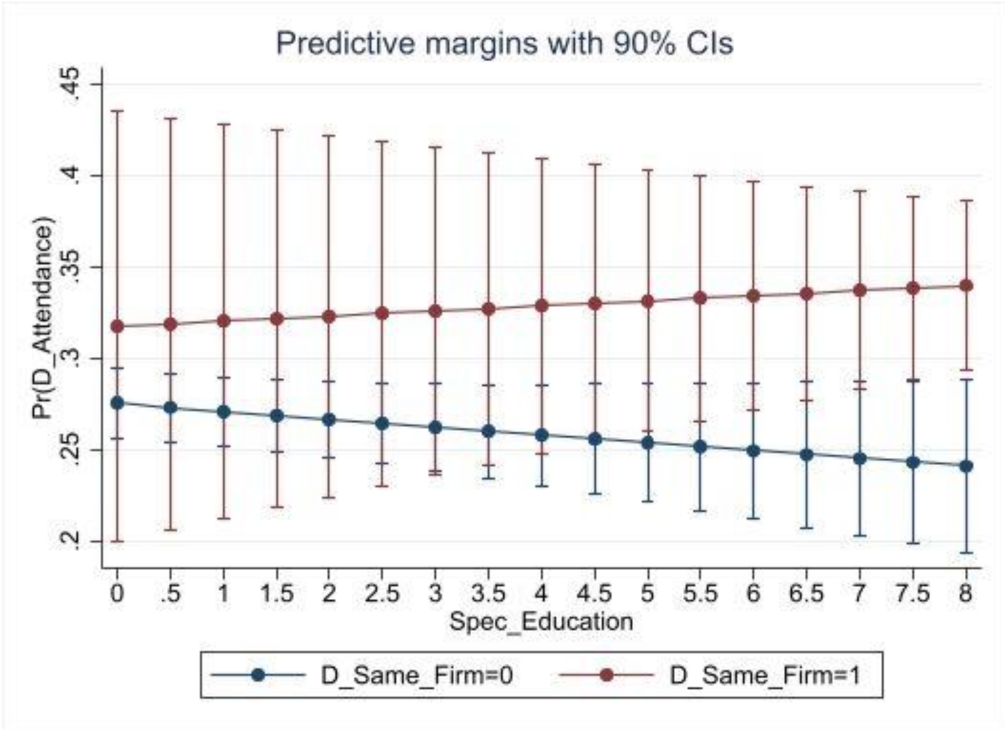
(a) *The Table lists probit regression coefficients and corresponding standard errors (in round brackets) for specific education variables. In column I, we report the coefficient when there is no common ground among team members and at least one of the teammates has specific education; in column II, when there is common ground among team members and at least one of the teammates has specific education. *** p<.01, ** p<.05, * p<.1.*

	D_Others_SE= 0 **D_Same_Firm= 0**	**D_Others_SE= 0** **D_Same_Firm= 1**
Spec_Education	-0.137 *** (0.023)	0.069 (0.129)

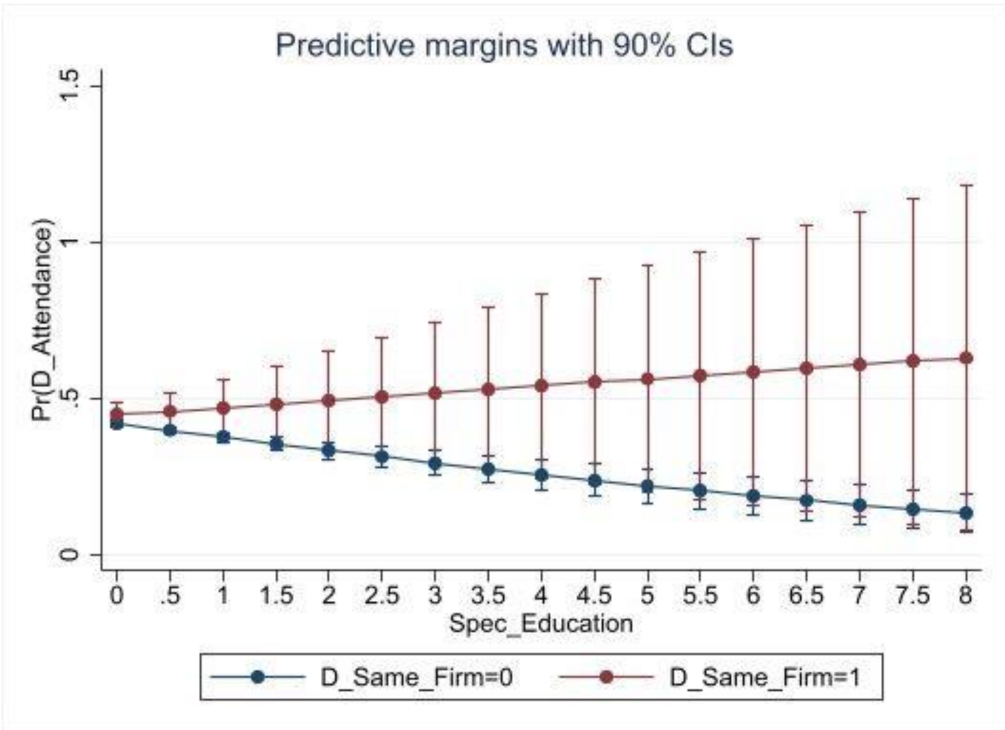
(b) *The Table lists probit regression coefficients and corresponding standard errors (in round brackets) for specific education variables. In column I, we report the coefficient when there is no common ground among team members and none of the teammates has specific education; in column II, when there is common ground among team members and none of the teammates has specific education. *** p<.01, ** p<.05, * p<.1.*

The three-way-interaction term has significant coefficient, meaning that there is a statistically significant interaction between the three variables taken into account. We plotted the relationship under analysis in Figure 5.3, which displays the predictive probability of attendance with regard to team members' competencies and common ground at various levels of specific education.

Figure 5.3: Predictive probability of attendance with respect to team members' competencies and common ground at various level of specific education



(a) D_Others_SE= 1



(b) D_Others_SE= 0

When at least one of the entrepreneur's teammates has specific knowledge in the domain (i.e., D_Others_SE=1), the slope of the regression line is **-0.016** (*P=0.252*) when there is no common ground among teammates (i.e., D_Same_Firm=0), and **0.009** (*P=0.646*) when there is common ground (i.e., D_Same_Firm=1). The coefficients of the independent variable are not significant in both cases (as it is possible to notice from the p-values in parentheses): this means that they are not (statistically different) from each other and that they are not even statistically different from zero. Thus, **hypothesis 3a is not confirmed**.

Instead, when teammates have no specific competencies and there is no common ground among teammates (i.e., D_Others_SE=0, D_Same_Firm=0), the coefficient of Spec_Education is negative and significant *(β=-0.137, P<.01).* Thus, the specific knowledge possessed by the entrepreneur impacts negatively the probability of attendance. Moreover, looking at the slope of the line **(-0.137),** the relationship presented in hypothesis 1 is strengthened. This could be related to the fact that, when team members lack common ground, more communication effort is required for coordination, and the likelihood of communication errors increases (Fast et al., 2009; Krifka, 2004). As a result, less knowledgeable entrepreneurs in a team with a knowledge gap may choose to invest more in training, knowing that it may be the only option to effectively learn new knowledge. When teammates have no specific competencies and there is common ground among teammates (i.e., D_Others_SE=0, D_Same_Firm=1), the slope of the regression line, which corresponds to the coefficient of Spec_Education, is equal to **0.069** (*P=0.594*). However, the coefficient is not significant once again, as evidenced by the graph. Indeed, even though the slope of the line is slightly positive, the graph shows that there are overlapping areas between confidence intervals (the higher the values of the independent variable, the more the confidence interval expands, mainly because there are few people with high specific education in the dataset); as a result, we cannot be certain that there is a growing trend. Thus, **hypothesis 3b is not verified**.

Results are counterintuitive. The significant interaction term communicates that the slopes differ from one another (Frazier et al, 2004). However, three out of the four regression lines have non-significant coefficients, so that we cannot reject the null hypothesis that their slope differs from zero. As a result, we have to conclude that common ground has no statistically significant effect on the relationship.

Results may have defied expectations for a variety of reasons. First, as previously mentioned, it might be attributable to sample characteristics (i.e., the specific education variable assumes predominantly low values). The nature of the common ground data we have might be another cause. Since we focused our research on a broad definition of common ground, we only whether each individual has previously worked in the same company as another team member, but not whether they really interacted with each other. there. Having shared professional experiences from different time periods may not be enough to assess how well colleagues know and trust one another, and hence how smooth knowledge transfer across peers is. Indeed, common experiences and knowledge are the necessary components for a successful exchange of information and the creation of a strong bond among teammates.

Overall, additional research may be needed to test the effect of common ground on the relationship between human capital investments and specific knowledge, to determine whether or not it provides a relevant moderation effect. For instance, the common ground variable may be designed to consider just the experiences that teammates have actually lived together.

5.4. Robustness check

We also performed a robustness check to test the hypotheses with alternative specifications and verify that the same findings hold under different assumptions. Therefore, we decided to run the econometric models again using a continuous dependent variable.

Throughout the training programme, we maintained track of entrepreneurs' attendance at each of the four lectures by checking the attendance report generated automatically by Microsoft Teams. This register tracked, in minutes, how long each participant stayed connected in the meeting for each training week. We derived from this data our dependent variable, called **Ln_Min_Attendance**, and we measured each entrepreneur's investment as his minutes of attendance at the lecture. Being the duration of each lecture 2 hours, attendance may range from 0 min (the entrepreneur never attended) to 120 min (the entrepreneur attended until the end the lecture).

We also performed data cleaning to obtain a reliable dataset. If the time was expressed also in seconds, we approximated it by excess if it was more than 30 seconds and by default if it was less than half a minute; additionally, when the participants' attendance exceeded the duration of the lecture (most likely because they forgot to exit the call, so the meeting lasted hours), we used 120 minutes as the standard value (as the total duration of a lecture was 2 hours).

Moreover, it was appropriate to apply a few transformations to the dataset to improve the linearity between dependent and independent variables and boost the validity of the statistical analyses.

Since the distribution of the dependent variable was positively skewed, we used its natural logarithm to reduce the skewness of the original data and make them more normal (values were increased by one to allow for the use of a logarithmic form). As the predicted values from a log-transformed regression can never be negative, the logarithmic transformation also respects the positivity of attendance, which, being a time metric, is by definition positive.

Table 5.8 contains a description of the variable.

Table 5.8: Description of continuous dependent variable

VARIABLE	TYPE	DESCRIPTION
Ln_Min_Attendance	Dependent variable	Continuous variable that reports the number of minutes the entrepreneur attended the lecture. It is a proxy of the entrepreneur's investment in human capital.

Having a continuous outcome variable, we ran a set of *OLS* regressions on Stata with robust standard errors to account for the problem of **heteroscedasticity** and clustered by module to account for the fact that there are four observations for each entrepreneur.

The results of the robustness check will now be described briefly. The findings of the empirical analysis conducted in relation to hypothesis 1 are displayed in Table 5.9. The coefficient of the specific education variable is negative and significant at 10% *(β=-0.072, P=.085)*, thus providing statistical evidence of a negative linear relationship between the human capital investments of an entrepreneur in a specific knowledge domain and the knowledge the entrepreneur already possesses in the domain. **Hypothesis 1 is confirmed**, even though the significance level is higher: the probability that an individual will attend a lecture diminishes as his level of expertise in the subject area in which he is acquiring new knowledge increases, due to the fact that returns decrease at an increasing rate as prior specific knowledge grows.

Furthermore, the effect of the control variables on the continuous dependent variable is similar to when the dependent variable is dichotomous.

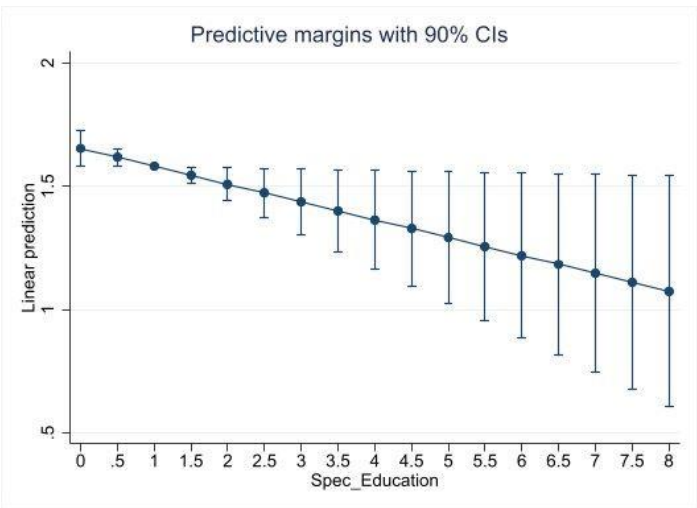
Table 5.9: Robustness check of H1

Ln_Min_Attendance	Coef.	St. Err.	Sig
Spec_Education	-.072	.029	*
D_Others_SE	-.56	.165	**
D_Same_Firm	.33	.043	***
Gen_Education	-.114	.026	**
D_Female	-.23	.12	
D_Other_Activity	-.242	.052	**
Ln_Team_Size	-1.032	.061	***
D_Others_Lecture	-.813	.418	
Module: base 1		.	
2	-.682	.067	***
3	-.788	.063	***
4	-.754	.088	***
D_Treatment	-.179	.088	
Constant	4.511	.141	***

*The Table lists OLS regression coefficients and corresponding standard errors (in round brackets) for each explanatory variable and the constant term. The outcome variable is a continuous variable that indicates the minutes of attendance of the entrepreneur at each lecture. The independent variable in is Spec_Education. *** p<.01, ** p<.05, * p<.1 Number of observations= 876*

This evidence is confirmed in Figure 5.4, which shows a graph that includes the predicted values of attendance for different levels of specific education, while holding the other variables at their mean.

Figure 5.4: Predicted values of attendance at different levels of specific education



Moving to hypothesis 2, detailed empirical results are shown in Table 5.10, whereas the relationship under analysis is plotted in Figure 5.5.

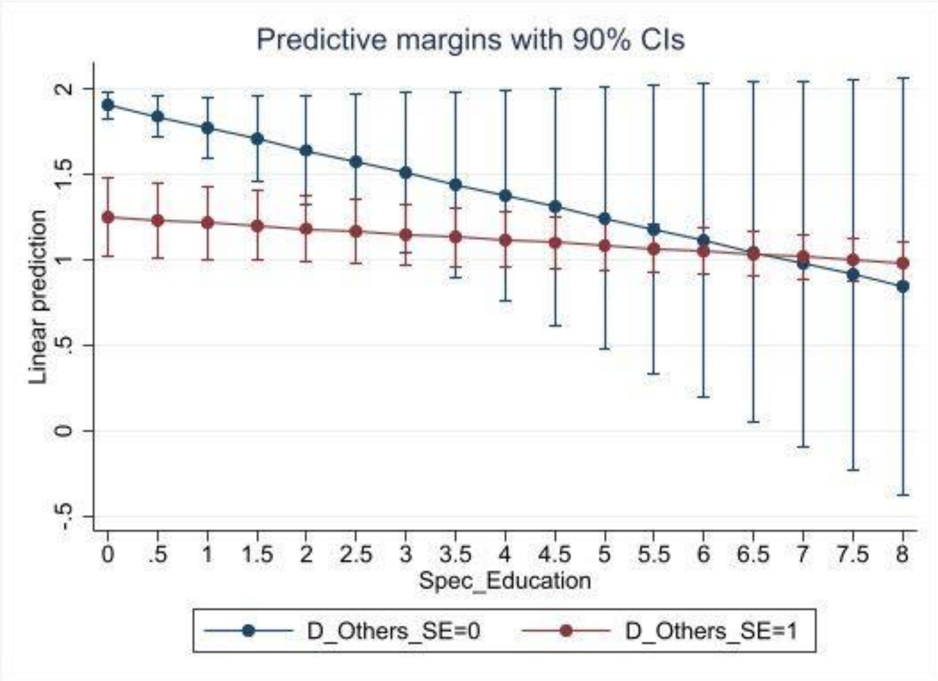
Results show that the two-way interaction term is not statistically significant *(P=.196).* Furthermore, when a moderation effect is added, the coefficient of the independent variable becomes non-significant (*P=.131*). As a result, using a continuous dependent variable, both **hypotheses 2a and 2b are not confirmed**: the moderation effect of team members competencies on the relationship is not statistically significant.

Table 5.10: Robustness check of H2

Ln_Min_Attendance	Coef.	St. Err.	Sig
Spec_Education	-.133	.064	
D_Others_SE	-.658	.125	**
Spec_Education# D_Others_SE	.099	.06	
D_Same_Firm	.316	.051	***
Gen_Education	-.114	.026	**
D_Female	-.217	.122	
D_Other_Activity	-.253	.051	**
Ln_Team_Size	-1.053	.073	***
D_Others_Lecture	-.797	.423	
Module: base 1		.	
2	-.68	.068	***
3	-.785	.064	***
4	-.751	.089	***
D_Treatment	-.167	.087	
Constant	4.566	.124	***

*The Table lists OLS regression coefficients and corresponding standard errors (in round brackets) for each explanatory variable and the constant term. The outcome variable is a continuous variable that indicates the minutes of attendance of the entrepreneur at each lecture. The independent variable in is Spec_Education and the moderator is D_Others_SE. *** p<.01, ** p<.05, * p<.1 Number of observations= 876*

Figure 5.5: Predicted values of attendance with respect to team members' competencies at various levels of specific education



Finally, talking about hypothesis 3, results are displayed in Table 5.11 and the relationship is plotted in Figure 5.6.

Looking at the findings, we discover that the three-way-interaction term is not statistically significant *(P=.128)* – which is not surprising, considering the non-significant results obtained testing hypothesis 2.

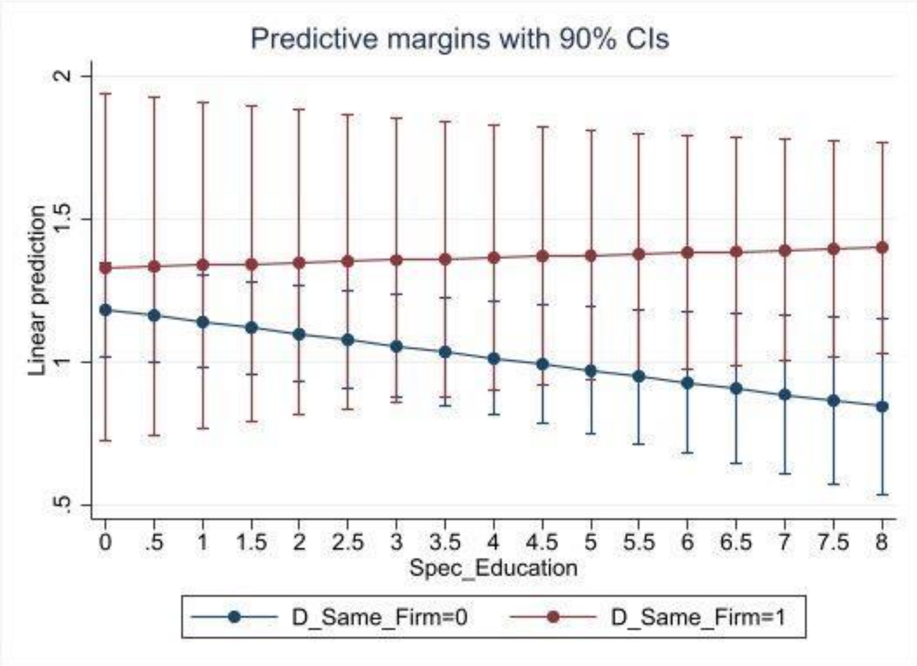
Thus, **hypotheses 3a and 3b are not supported**: common ground does not provide a statistically significant moderation effect of on the relationship.

Table 5.11: Robustness check of H3

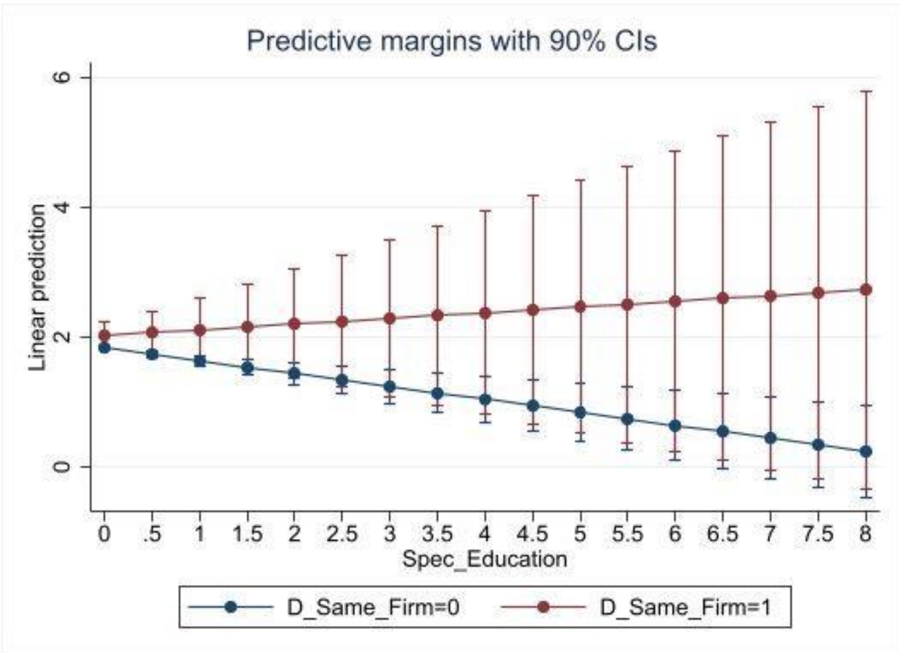
Ln_Min_Attendance	Coef.	St. Err.	Sig
Spec_Education	-.199	.039	**
D_Others_SE	-.652	.07	***
Spec_Education# D_Others_SE	.157	.041	**
D_Same_Firm		.	
1	.191	.094	
D_Same_Firm# Spec_Education		.	
1	.286	.125	
D_Same_Firm# D_Others_SE		.	
1	-.043	.346	
D_Same_Firm# Spec_Education#D_Others_SE		.	
1	-.235	.114	
Gen_Education	-.106	.026	**
D_Female	-.236	.112	
D_Other_Activity	-.238	.037	***
Ln_Team_Size	-1.05	.069	***
D_Others_Lecture	-.771	.43	
Module: base 1		.	
2	-.676	.069	***
3	-.781	.065	***
4	-.745	.09	***
D_Treatment	-.164	.084	
Constant	4.548	.116	***

*The Table lists OLS regression coefficients and corresponding standard errors (in round brackets) for each explanatory variable and the constant term. The outcome variable is a continuous variable that indicates the minutes of attendance of the entrepreneur at each lecture. The independent variable in is Spec_Education and the moderator is D_Others_SE and D_Same_Firm. *** p<.01, ** p<.05, * p<.1 Number of observations= 876*

Figure 5.6: Predicted values of attendance with respect to team members' competencies and common ground at various level of specific education



(a) D_Others_SE=1



(b) D_Others_SE=0

Overall, the results of the robustness check partially contradict the findings obtained in the main analysis. Indeed, while hypothesis 1 is confirmed using both dependent variables, hypothesis 2a is validated only when a dichotomous variable (i.e., D_Attendance) is employed.

However, we believe that the non-significance of the results obtained in the robustness check may be related to the fact that the attendance data we collected are subject to potential bias, related either to entrepreneurs' private life or training conditions. Concerning the first category, some entrepreneurs' low attendance may have been caused by external factors such as illness or the presence of another important commitment at the same time as the lecture. Regarding the second category, training time data may have been altered by connection drops during the course, problems entering the meeting, or entry and exit from break-out rooms.

In conclusion, further research is required to increase the validity of our inferences: researchers should test whether the estimated effects obtained in our baseline model are sensitive also to different changes in model specifications. This would allow us to discern whether robustness check results are contaminated by some bias.

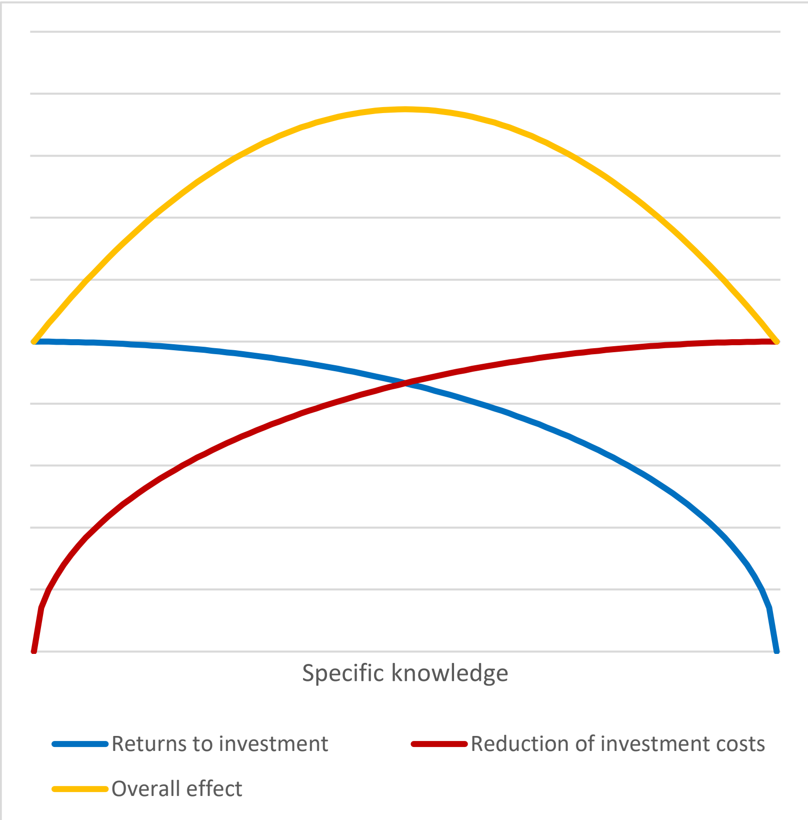
5.5. Additional analyses

5.5.1. Inverse U-shaped investment curve

As discussed in chapter 3.3, the choice of investing in human capital is governed by the returns that the investment generates at start-up and individual's level: as the entrepreneur's knowledge in a specific knowledge domain increases, the expected returns on his human capital investment decrease at an increasing rate. However, we believe that the decision to invest in human capital may be influenced also by investment costs, which decrease at a decreasing rate as domain knowledge increases.

As a result, by summing the shape of the returns to investment curve and reduction of investment costs curve, we obtain an inverse U-shaped relationship between human capital investments in a specific knowledge domain and entrepreneur's prior knowledge in the domain (see Figure 5.7). As entrepreneur's level of specific knowledge increases, so does his probability to invest. However, with very high levels of specific knowledge, the favourable effect of having extra prior knowledge vanishes, and expected attendance probability decreases. As a result, we can say that an investment in human capital yields the highest expected returns until a certain level of specific knowledge is reached: in the first part of the graph, where the entrepreneur is less knowledgeable, he will benefit from a high return on investment, but he will also need to commit a significant amount of time in order to acquire the new knowledge (i.e., high opportunity cost of investing time to skill/knowledge acquisition rather than working in the venture). Instead, in the second part of the graph, where the entrepreneur is more knowledgeable, he will benefit from a faster learning process (as acquiring information in a known area takes less time than acquiring knowledge in an unknown domain), even if the returns on investment of the acquired know-how will be modest due to his pre-existing competencies.

Figure 5.7: Inverse U-shaped investment curve



Therefore, we hypothesize the following relationship:

Hypothesis 4: *There is an inverse U-shaped association between the human capital investments of an entrepreneur in a specific knowledge domain and the knowledge the entrepreneur already possesses in the domain.*

The associated statistical model is as follows:

$$Prob(D\_Attendance) = b_0 + b_1 Spec\_Education + b_2 Spec\_Education^2 + \gamma Controls + \varepsilon$$

According to H4, we expect a positive and significant coefficient of b_1 and a negative and significant coefficient of b_2, thus indicating an inverse U-shaped relationship between the independent and the dependent variable. Indeed, a significant quadratic trend exists if the regression coefficient b_1 is statistically different from zero; moreover, if b_2 is negative, the relationship resembles an inverted U.

The results of the statistical models for hypothesis 1 are shown in Table 5.12.

Table 5.12: Quadratic regression results for H1

D_Attendance	Coef.	St. Err.	Sig
Spec_Education	-.067	.043	
Spec_Education^2	.004	.006	
D_Others_SE	-.365	.126	***
D_Same_Firm	.215	.038	***
Gen_Education	-.075	.017	***
D_Female	-.143	.102	
D_Other_Activity	-.184	.043	***
Ln_Team_Size	-.709	.034	***
D_Others_Lecture	-.556	.29	*
Module: base 1		.	
2	-.442	.063	***
3	-.569	.061	***
4	-.511	.07	***
D_Treatment	-.15	.07	**
Constant	1.604	.156	***

*The Table lists probit regression coefficients and corresponding standard errors (in round brackets) for each explanatory variable and the constant term. The outcome variable is a dichotomous variable that assumes a value of 1 if the entrepreneur attended the lecture, and 0 otherwise. The independent variable in is Spec_Education. *** $p<.01$, ** $p<.05$, * $p<.1$. Number of observations= 876*

The results show that the linear term of the independent variable is negative and not significant *(P=.125),* whereas the squared term is positive and not significant *(P=.487).* Since the independent variables' coefficients are not statistically significant, **hypothesis 4 is not validated.** Thus, we can conclude that the probability of attending the course is not influenced by investment costs; the only proven association is the negative linear relationship between attendance and specific knowledge.

One possible explanation for the variables' non-significance is that characteristics of the sample caused the results to differ from our predictions: indeed, the specific education variable lacks diversity, which is confirmed by the fact that 55% of the entrepreneurs do not hold economic or management degrees.

Another justification is that people with different degrees of specific education do not exhibit significantly different absorptive capacity (and, hence, they do not suffer significantly different investment costs). Investment costs most likely differ between individuals who have never studied and those who have a degree, but not between individuals who hold a first-level degree and those who have a PhD.

Overall, further study may be required to test the hypothesis; additionally, a different independent variable, such as one related with specific knowledge acquired at the workplace, may be used.

5.5.2. Extensiveness of the common ground among founders

By reviewing the literature, we discovered that academics rarely propose a quantitative definition of common ground: this topic has usually been studied with an emphasis on its theoretical definition rather than its measurable characteristics. For this reason, we decided to try to define common ground as a continuous variable and use it to test hypothesis 3.

As described in chapter 4.7.4, we tried to devise a proxy for the initial common ground. We recorded, in years, how much time each participant spent at the same university or workplace as other team members, even in different time periods. The next step was to operationalise this data in order to create two separate variables, called **Edu_CG** and **Work_CG** (see Table 5.13).

Table 5.13: Description of variables quantifying the extensiveness of common ground

VARIABLE	TYPE	DESCRIPTION
EDU_CG [years]	Moderator variable	For each start-up, it identifies the extensiveness of the common ground among founders, expressed in years, referring to previous shared academic experiences.
WORK_CG [years]	Moderator variable	For each start-up, it identifies the extensiveness of the common ground among founders, expressed in years, referring to previous shared professional experiences.

To accomplish this, after a careful review of the extant literature we selected as a reference a study published in 2016 by Zheng, Devaughn and Zellmer-Bruhn, called "Shared and shared alike? Founders' prior shared experience and performance of newly founded banks".

In their empirical study, the authors use a **relational approach** to measure PSE (i.e., Prior Shared Experience) extensiveness. As previously explained in chapter 2.2.5.4, we may think of PSE as another definition of common ground; moreover, PSE varies in "extensiveness", which increases as entrepreneurial team members' shared experience lengthens (Zheng et al., 2016). At one extreme, all founders may have gained their experience independently in different contexts; at the other extreme, the entire team may have always studied and worked together before creating the start-up, as in the case of a university-based spin-out, where team members think more similarly since they have shared comparable experiences (Rentsch and Klimoski, 2001). Most teams are most likely somewhere in the middle (Huckman et al., 2009).

In the same way, we used a relational approach to calculate the extensiveness of the common ground among founders. For each start-up, we first defined the number of dyads of founders (i.e., couples) on the basis of the entrepreneurial team size. Using the data already gathered from LinkedIn, we captured the length of their shared academic experience as Tu_{ij} (being i and j any two founders from the same start-up) and shared professional experience as Tf_{ij}. Given that we had two values for each dyad (indeed, we had recorded the time spent in the same university/workplace by each founder), we decided to pick the smallest of the two figures, in order to be conservative and consider just the time period during which they may have developed similar thinking by living comparable experiences. Then, we summed all Tu_{ij} for all dyads to arrive at a total duration of shared academic experience in the team and divided this sum by the number of dyads in the founding team. This way, we obtained the value of the variable Edu_CG for each start-up. Work_CG was calculated using comparable logic and Tf_{ij} values.

As an example, let's consider a hypothetical start-up with three members composing its entrepreneurial team: A, B, and C. Regarding their education, we know that Founder A attended Politecnico di Milano from September 2017 to September 2022, where he earned both his bachelor's and master's degrees; Founder B, instead, completed his bachelor program at Politecnico di Milano in 2015 and then started working; finally, Founder C never went to university. In this case, we have three dyads: A–B, B–C, and A–C. The only dyad with previous shared experience is A-B, as both Founder A and Founder B attended Politecnico di Milano, albeit at separate moments. Since Founders A and B spent 5 and 3 years there, respectively, and we pick the minimum figure between the two, Tu_{AB} would be 3 years. The value of the Edu_CG variable for the start-up is therefore 1, or 3 divided by 3.

We tested hypotheses 3a and 3b using these new variables. Tables 5.14 and 5.15 summarize the findings of the econometric analysis.

Table 5.14: H3 testing using the extensiveness of the common ground among founders referring to previous shared academic experiences

D_Attendance	Coef.	St. Err.	Sig
Spec_Education	-.085	.04	**
D_Others_SE	-.283	.128	**
Spec_Education#D_Others_SE	.078	.053	
Edu_CG	.007	.009	
Spec_Education#Edu_CG	.004	.011	
D_Others_SE#Edu_CG	-.022	.055	
Spec_Education#D_Others_SE#Edu_CG	-.006	.023	
Gen_Education	-.036	.022	
D_Female	.045	.07	
D_Other_Activity	-.168	.024	***
Ln_Team_Size	-.663	.023	***
D_Others_Lecture	-.394	.261	
Module: base 1		.	
2	-.379	.047	***
3	-.55	.052	***
4	-.541	.059	***
D_Treatment	.01	.055	
Constant	1.23	.088	***

*The Table lists probit regression coefficients and corresponding robust standard errors (in round brackets) for each explanatory variable and the constant term. The outcome variable is a dichotomous variable that assumes a value of 1 if the entrepreneur attended the lecture, and 0 otherwise. The independent variable in is Spec_Education and the moderators are D_Others_SE and Edu_CG. *** p<.01, ** p<.05, * p<.1. Number of observations= 876*

Table 5.15: H3 testing using the extensiveness of the common ground among founders referring to previous shared professional experiences

D_Attendance	Coef.	St. Err.	Sig
Spec_Education	-.07	.033	**
D_Others_SE	-.173	.152	
Spec_Education#D_Others_SE	.052	.05	
Work_CG	.03	.013	**
Spec_Education#Work_CG	-.01	.008	
D_Others_SE#Work_CG	-.16	.031	***
Spec_Education#D_Others_SE#Work_CG	.029	.024	
Gen_Education	-.033	.024	
D_Female	.069	.081	
D_Other_Activity	-.151	.023	***
Ln_Team_Size	-.669	.02	***
D_Others_Lecture	-.418	.267	
Module: base 1		.	
2	-.386	.05	***
3	-.559	.055	***
4	-.55	.062	***
D_Treatment	-.042	.047	
Constant	1.225	.106	***

*The Table lists probit regression coefficients and corresponding robust standard errors (in round brackets) for each explanatory variable and the constant term. The outcome variable is a dichotomous variable that assumes a value of 1 if the entrepreneur attended the lecture, and 0 otherwise. The independent variable in is Spec_Education and the moderators are D_Others_SE and Edu_CG. *** p<.01, ** p<.05, * p<.1. Number of observations= 876*

It is immediately evident that in both tables the three-way interaction terms are not statistically significant. As a result, **hypotheses 3a and 3b are not confirmed**: the moderation effect of common ground on the relationship is not statistically significant.

A non-significant result, however, does not necessarily imply that there is no effect in the sample: it just indicates that there is insufficient evidence in the dataset to conclude that there is an effect. Therefore, further research could consider employing a larger dataset, as well as modelling in a different way the common ground variable (as stated in chapter 5.3.2, considering shared experiences from different time periods may not be the most appropriate way to shape common ground among team members).

6 Conclusions

6.1. Discussion

The transition to the scaling phase is one of the most critical stages of a company's growth. Scaling appears to be attainable only if team members possess the necessary expertise to aid the firm in growing and if they succeed in communicating and coordinating the various activities. Thus, human capital, especially when it relates to the knowledge required to run the business, and common ground among team members are essential components for a start-up expansion.

Typically, start-ups face a liability of newness due to a lack of capabilities and resources (Cafferata et al., 2009). The missing competencies can be acquired through human capital investments, which increase the productivity of peers and can considerably improve the company's performance.

Because the above-described concepts are so crucial to the success of a start-up, we decided to investigate in this dissertation the relationship between entrepreneurs' human capital investments and the human capital they possess, taking into account also the effect of team members' competencies and common ground. Specifically, the central research question was the following:

How do entrepreneurs' human capital and common ground affect the human capital investments made within a start-up?

The purpose of the study was to combine two separate levels, namely the individual level and the entrepreneurial founding team level. Therefore, we chose to depict the entrepreneur's decision to invest in human capital as driven by both individual and start-up team's characteristics.

In order to test our hypotheses, we joined the InnoVentureLab research team and helped them organize a randomized control trial (RCT) that involved 151 Italian ventures in the pre-scaling phase. The training program was structured into four online sessions and aimed to transfer methodologies regarding the management of financial resources. We participated to the lectures as research assistants, monitoring entrepreneurs' participation throughout the program. We collected and analysed data from questionnaires and direct calls, focusing on the measurement of founders' specific knowledge in the domain of the course. Specifically, we defined it as the years of academic education in economical, management or entrepreneurial areas. We also quantified the level of common ground among team members, considering if they had worked in the same firm even in different time periods.

Our econometric analyses showed the presence of a small but significant negative linear relation between the level of specific knowledge of entrepreneurs and the probability to invest in human capital (i.e., the likelihood of attending a lecture), which confirmed our first hypothesis. In terms of marginal effects, the probability of attending the lecture will drop by 1.29 percentage points if entrepreneur's specific education increases by one year. We argue that the main reason for this result pertains to the returns associated with the human capital investment, which include start-up benefits as well as personal benefits. Indeed, when entrepreneurs have a low degree of specific education, human capital investments in the domain deliver great projected returns, and the probability to attend is therefore very high. Predicted returns decrease at an increasing rate as domain competence increases: the more informed entrepreneurs are about the subject, the less they will invest, as their prior competencies make it less advantageous for them to attend the course.

We then identified two moderators related to entrepreneurial founding team’s characteristics that could affect the principal relation. More precisely, to test hypotheses 2a and 2b we studied the interaction effect of team members’ competencies, and to test hypotheses 3a and 3b we added the effect of the presence of common ground among team members.

Hypothesis 2b was verified. The empirical analysis showed that when the entrepreneurial team has a substantial knowledge gap in the domain (i.e., no one of the teammates has economics, managerial or entrepreneurial competencies), the original linear decreasing relationship steepens (the slope of the regression line goes from -0.042 to -0.087), implying that there is a higher likelihood that the entrepreneur will invest in human capital when he has low levels of prior knowledge. This is because the venture's expected positive returns are higher: indeed, the new knowledge and skills acquired by the entrepreneur will benefit everyone within the start-up by filling at least partially the knowledge gap of peers. Hypothesis 2a, instead, was not verified. Empirical results were in line with our assumptions, showing that, when at least one of the entrepreneur’s teammates has economic, managerial or entrepreneurial knowledge, the linear decreasing relationship between an individual's likelihood of participating in the lecture and their specific knowledge flattens. This should occur because, while there is no complete knowledge gap to be filled, obtaining new competencies in this subject would allow the entrepreneur to better communicate with his teammates by building new common ground. However, the hypothesis was rejected because the independent variable's coefficient was not statistically significant.

Both hypotheses 3a and 3b were not validated due to the lack of statistical significance. Indeed, from our analyses it resulted that common ground among teammates does not have a statistically significant impact on the principal relationship. Empirical results defied our expectations, according to which the likelihood of investing in human capital should increase as the entrepreneur's specific competencies grow when there is common ground among team members. Indeed, the most cost-effective option for the start-up would be let experienced team members attend the course and then share what they learn with their colleagues: this is advocated because more knowledgeable members can obtain new information at a reduced cost due to their greater absorptive capacity, and they can successfully transfer knowledge to peers thanks to the high common ground, which facilitates communication inside the start-up.

Common ground is related to knowledge transfer, which in turn may impact the decision to invest in human capital. As a result, regardless of the type of influence, it is odd that there is no impact on the relationship; additional research may be required to reconcile theoretical explanations with empirical results. The limited number of observations and low heterogeneity in the personal characteristics of the entrepreneurs are possible explanations for the result's insignificance. Another reason could be the nature of the common ground data, which does not indicate whether team members who worked in the same firm actually interacted with each other there: shared professional experiences from different time periods may not be a reliable proxy for defining team members' common ground, and hence how smooth knowledge transfer among peers is.

We then ran a robustness check, in which we tested our hypotheses with a continuous dependent variable rather than the previously employed dichotomous dependent variable, to ensure that the same results held true under other assumptions. The robustness check results partially contradicted the findings of the main analysis: hypothesis 1 was confirmed, but hypothesis 2a was rejected. Furthermore, the interaction terms were never found to be statistically significant, showing that neither team members' competencies nor common ground have a statistically significant moderation effect on the relationship.

Of course, further research is needed to improve the validity of our baseline model's inferences; however, we believe that the non-significance of the results obtained in the robustness check may be due to the fact that the attendance data we collected are subject to potential bias (for instance, attendance data may have been altered by connection drops during the lectures).

Finally, we conducted two further analyses. First, we attempted to determine whether investment costs influence the decision to invest in human capital. As a result, we postulated an inverse U-shaped relationship between human capital investments in a specific knowledge domain and the prior knowledge of the entrepreneur in the domain (obtained by summing the shape of the returns to investment curve and reduction of investment costs curve). However, due to the non-significance of the results, this hypothesis was rejected. Second, we tested hypotheses 3a and 3b using two different continuous common ground variables, assessing the extensiveness of common ground among founders (expressed in years) referring to previous shared academic and professional experiences. Also in this case, Hypotheses 3a and 3b were rejected due to non-significant results.

6.2. Conclusive Remarks

In this chapter, we point out the main contributions we bring to the entrepreneurship literature. Besides, we mention the main limitations of our work as well as possible future research path.

6.2.1. Theoretical and practical implications

In this dissertation, we bring substantial theoretical contributions to the current literature. To begin, our study enriches the body of human capital entrepreneurship literature by investigating an unusual set of start-ups, specifically those in the pre-scaling phase. Indeed, despite the fact that the terms scaling and pre-scaling are widely used, a clear definition of these concepts still does not exists: scholars disagree on the metrics that characterize the scaling phase, and the pre-scaling phase is hardly addressed in the literature. This work has tried to clarify the distinction between start-ups and scale-ups by summarizing the metrics that identify their boundaries and it has then focused on the phase between them and attempted to define it both qualitatively and quantitatively. Besides, since pre-acceleration programs are less diffused than incubators and accelerators, there is limited research on them in the literature. However, knowledge imparted by pre-accelerator programs at this stage of the start-up life cycle might have a significant impact on future entrepreneurial activities.

This research also adds to the existing studies on the dynamics of human capital investments made by start-ups by focusing on both personal and entrepreneurial team characteristics. Indeed, we have investigated how entrepreneurs' previous human capital in a domain influences further investments in that domain and how teammates' prior human capital and interpersonal characteristics moderate this relationship. By using a moderator approach, we have tried to address a research gap found in the literature, where the interplay between human capital and common ground is not commonly discussed.

Overall, we provide an answer to the fundamental question of what factors influence start-ups' decisions to acquire additional human capital in a knowledge area. The work focuses on a specific knowledge domain, namely entrepreneurial finance, because acquiring and integrating novel competences in this area may be beneficial to the growth of start-ups. We discovered that entrepreneurs' investments in human capital are influenced by the returns they believe they may achieve at the individual and start-up levels, which are in turn tied to their prior specific knowledge of the subject. Because the relationship is negative and linear, the likelihood of entrepreneurs investing and acquiring new knowledge reduces proportionally as their expertise increases. However, other elements must be investigated in addition to previous knowledge to completely comprehend the investment decision process. Indeed, it must be considered that the entrepreneur is part of a larger entity, namely the start-up. For this reason, we concentrated on the characteristics of the entrepreneurial team and discovered that the level of competencies of team members plays a significant role; nevertheless, common ground among team members has no effect on the relation.

From a managerial perspective, start-up's members need to develop the competencies of their venture as it matures; to do this, they typically have to acquire new knowledge by investing in human capital. Indeed, high human capital may contribute to the creation of competitive advantage, especially when it enables the start-up to reach the scaling phase of the life cycle. As a result, one of the primary concerns of an entrepreneurial team is acquiring the skills and knowledge required for the growth of the firm. However, what is the level of human capital investment that start-up members consider to be appropriate? And who is in charge of making the investment? Based on the analysis, it can be concluded that the members who invest more in human capital are the ones having less expertise in the domain in which new knowledge is acquired; furthermore, the likelihood of investing is affected by the entrepreneurial team's overall level of knowledge in the domain.

6.3. Limitations and Future Research

We took several measures to counteract potential problems linked to our research. For instance, we used human capital indicators from the literature and tested potential confounds to see if they caused artificial differences. However, we acknowledge that our study has some limitations, which may realistically open the path to future research.

To begin, there are some constraints on the generalizability of our results, which are linked to the way the selection process was conducted. Indeed, the start-ups involved in the training mainly come from Northern Italy, as they were contacted exploiting the relationship network of Politecnico di Milano, Politecnico di Torino and Bocconi. In addition, the pre-acceleration program may have admitted ventures that were not yet in the pre-scaling stage– it should be remembered that the concept of pre-scale-up in the entrepreneurial literature remains ambiguous. Additional studies on the definition of pre-scaling ventures and the use of a more heterogeneous sample may benefit the generalizability of future research's results.

Second, in addition to having considered a broad definition of common ground, our common ground variables do not take into account when the shared experience dates back. According to Klein et al. (2005), common ground is not a binary or constant feature; instead, it is both continuous in its degree and constantly changing over time. To enable successful exchange of information, it should be continually inspected and adjusted to avoid its degradation during team interactions. Furthermore, it should be noted that the spread of smart-working has profoundly modified interpersonal interactions, altering how colleagues communicate with one another and how information is transferred. As a result, additional research on group dynamics would enable us to quantify the true common ground among team members.

Another limitation concerns the fact that the results of the robustness check partially contradict the findings obtained in the main analysis. In this regard, further studies may solve these issues using a more robust proxy of human capital investments; for instance, it could be relevant to collect attendance data relative to longer training periods (e.g., training composed by more lectures or longer lectures). This would allow us to discern whether our results are contaminated by some bias or if they are instead generalizable to human capital investments' decisions in general.

Overall, this work may be intended as a starting point to widen the study of the dynamics of human capital investments within start-ups. Further research could deepen the relationship between human capital investments and specific knowledge by employing different proxies of specific knowledge, such as the length of previous experiences in the entrepreneurial field as well as the length of working experiences in financial and administrative roles. Moreover, it may be worthwhile to investigate whether our findings apply equally to ventures in different stages of the life cycle, such as early-stage start-ups or established businesses.

Doubtlessly, the unexpected results obtained testing hypothesis 3 clearly require additional explanation. The fact that common ground does not appear to impact the relationship is intriguing and should be investigated further; it may be interesting for other researchers to discover whether or not this moderator has actually any effect. Finally, future research may benefit from examinations of firm-level human capital conceptualizations (Marvel et al., 2016).

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7 Appendix

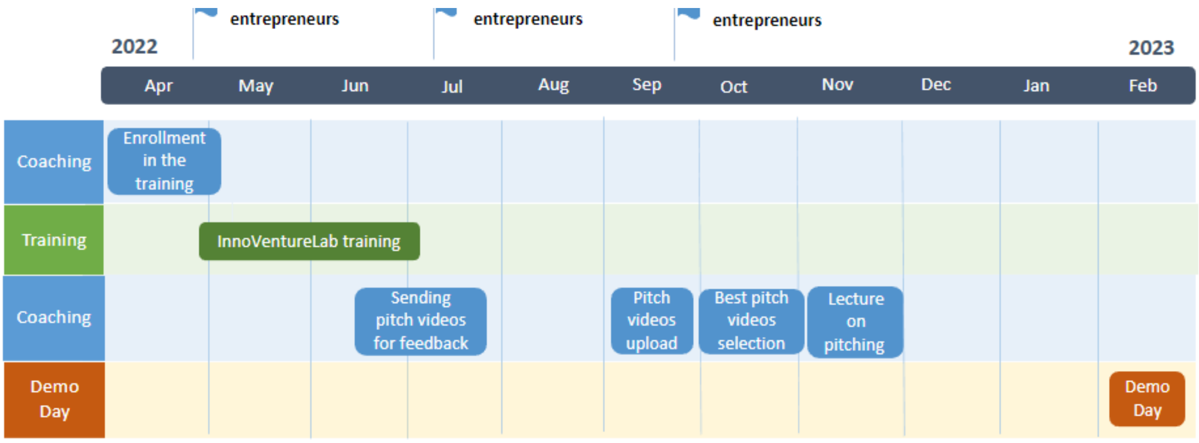
7.1. Appendix A

"Scientific" entrepreneurs follow a five-step process in making decisions (Coali et al., 2021), described in Table 7.1.

Table 7.1: Scientific decision-making process (Coali et al., 2021)

Step	Description
Theory development	Scientific entrepreneurs begin by considering the problem that their start-up is facing. They then develop a theory of the problem and select key elements on which to focus. They also examine how the value of their actions might change in different relevant scenarios.
Hypotheses formulation	Based on the theory, they create some basic hypotheses about the scenarios their start-up may face and the value of actions in such scenarios. Hypotheses should be testable and falsifiable.
Hypotheses testing	They test such hypotheses via carefully designing tests, collecting representative and appropriate data and conducting rigorous experiments.
Results evaluation	The results of the tests can be used by scientific entrepreneurs as "signals" to assess the value of their idea. Signals are systematically compared to theory and past beliefs.
Final decision	They eventually decide whether it is worth to continue developing their idea, to terminate the project, or to pivot.

Figure 7.1: InnoVentureLab's Roadmap



In Table 7.2, the script of the second round of interviews is reported. The emphasis is mostly on the recent changes in start-ups' business model and financial strategy.

Table 7.2: Interviews' script

Topic	Question
Ice-breaker	Define content of the interview. Specify how data will be used by InnoVentureLab.
Start-up's business model	Describe the changes you have made to your startup's value proposition. How have the potential customers of your startup changed? Have you identified additional problems/needs of these customers? How has the key benefit your startup offers to customers changed?
Start-up's business model	Describe the changes you have made to your startup's business model. How have the activities that your startup has to carry out according to its value proposition changed? How have the resources needed to implement the startup's value proposition changed?
Start-up's business model	What new resources has the startup acquired? Have you acquired new human resources by hiring new employees/managers or involving new partners? Have you bought new machinery? Have you developed or licensed patents? Have you developed partnerships with other companies?

Start-up's business model	Have you identified any resources that you had not previously thought of that are useful for the development of the startup's business model? If so, how do you think you have access to it?
Start-up's financial strategy	Have you recently (re)thought about how much capital your start-up needs to realize its development plan in the next 3 years? If so: what is the new value?
Start-up's financial strategy	How did you calculate the value of the capital needed for the startup and how do you plan to allocate this capital among the possible uses (e.g., purchase of equipment, purchase of consulting services, hiring more people or people with more qualified skills, investments in market analysis, etc.)
Start-up's financial strategy	Have you recently (re)thought about which sources of funding you intend to use to finance your startup in the next 3 years and how much capital do you hope to raise from each source?
Start-up's financial strategy	How much equity capital do you intend to raise? Which sources of equity capital do you intend to use and what is their weight on the total equity capital raised? Choose in the following list: Family & Friends, Equity crowdfunding, Business angels, Venture capital, Equity from companies, Other equity (please specify)
Start-up's financial strategy	How much debt capital do you intend to raise? Which sources of debt capital do you intend to use and what is their weight on the total debt capital raised? Choose in the following list: Personal debts incurred by entrepreneurs, Debts of family and friends, Bank debt
Start-up's financial strategy	Why do you think that the sources of funding you have mentioned are the most appropriate given the business model and development plans of your startup? To identify these sources of funding, did you collect any data? If so, what data did you collect and how did you analyze it? If not, was it based on personal or friends' knowledge and experience? Have you used the services of a financial advisor?
Start-up's financial strategy	Do you think there is any problem in collecting the desired amount from the sources of funding indicated above? In the event that you fail to pursue the funding strategy described (for example due to difficulties in accessing the sources of financing chosen as ideal), have you thought about how it could change the business model of your startup? Have you evaluated alternative sources of

	funding compared to those you mentioned earlier? If so, which ones? What kind of considerations and analysis did you do to get to discard these alternative sources?
Conclusion	Thank the entrepreneur. Give updates on the next steps of the InnoVentureLab program.

The elements on which we based our scoring to evaluate the scientific approach of the respondents are presented in Table 7.3. We utilised a Likert scale with ratings ranging from 1 to 5. 1 indicates that no evaluation was made; 3 implies that an approximate assessment was performed; and 5 denotes that a precise assessment was conducted.

Table 7.3: Interviews' coding system

Variable	What to codify	How to codify	SCORE (1-5)
Clear theory	The theory is understandable (falsifiability)	Score to be given at the end if the exposure was clear 1 = it is not clear how he defined the sources of financing to be used and their amount 5= the process that led to the definition of the sources of funding to be used and the amount to be raised for each is very clear	
Elaborated theory	The theory goes into detail (falsifiability)	If he considered problems and pros and cons of the various sources, the theory is elaborated	
Alternative theory	The theory considers alternative aspects (generalizability)	1=respondent did not consider alternative sources or develop a plan B 5= the respondent evaluated alternative sources and developed a plan B	

Theory evidence	The theory has data that support it	1=the respondent did not collect any data to define the ideal sources 5= the respondent collected sensible data and analyzed it convincingly	
Modular theory	The theory breaks down the problem into sub-problems to be solved	1= the problems to be solved have not been made modular in any way 5= the respondent considered the business model as a constraint and optimized the financial choices; in the event that the solution is not satisfactory, he has changed the business model, given the financial constraints	
Hierarchical theory	The theory helps prioritize the problems to be solved	1= there is no element that leads to say that the respondent has prioritized some element over others 5= the respondent set priorities with respect to problems to be solved (e.g., first, he understood whether to bet on debt or equity, then he defined the specific sources for the chosen financial instrument. Another example: the respondent is rich, so he chose to focus primarily on equity and then evaluated whether to look for debt or equity)	

7.2. Appendix B

Table 7.4: Predictive margins of D_Attendance at different values of Spec_Education

Spec_Education	Margin	St. Err.	Sig.
0	0.377	0.005	***
0.5	0.371	0.002	***
1	0.364	0.002	***
1.5	0.358	0.004	***
2	0.352	0.007	***
2.5	0.345	0.009	***
3	0.339	0.012	***
3.5	0.333	0.015	***
4	0.327	0.017	***
4.5	0.320	0.020	***
5	0.314	0.022	***
5.5	0.308	0.025	***
6	0.302	0.027	***
6.5	0.296	0.029	***
7	0.291	0.032	***
7.5	0.285	0.034	***
8	0.279	0.036	***

Table 7.5: Predictive margins of D_Attendance at different values of Spec_Education, considering the effect of teammates competencies

	Teammates without competencies (*D_Others_SE=0*)			Teammates without competencies (*D_Others_SE=1*)		
Spec_Education	**Margin**	**St. Err.**	**Sig**	Margin	std.	Sig
0	0.432	0.009	***	0.292	0.023	***
0.5	0.418	0.012	***	0.291	0.022	***
1	0.403	0.017	***	0.289	0.021	***
1.5	0.389	0.023	***	0.287	0.020	***
2	0.376	0.028	***	0.286	0.019	***
2.5	0.362	0.034	***	0.284	0.018	***
3	0.348	0.039	***	0.283	0.017	***
3.5	0.335	0.045	***	0.281	0.016	***
4	0.322	0.050	***	0.279	0.016	***
4.5	0.309	0.055	***	0.278	0.015	***
5	0.296	0.059	***	0.276	0.015	***
5.5	0.284	0.064	***	0.274	0.015	***
6	0.272	0.068	***	0.273	0.015	***
6.5	0.260	0.072	***	0.271	0.015	***
7	0.248	0.075	***	0.270	0.015	***
7.5	0.237	0.078	***	0.268	0.015	***
8	0.226	0.081	***	0.267	0.015	***

Table 7.6: Predictive margins of D_Attendance at different values of Spec_Education, considering the effect of teammates competencies and common ground

	Teammates without competencies No common ground (*D_Others_SE=0, D_Same_Firm=0*)			Teammates without competencies Presence of common ground (*D_Others_SE=0, D_Same_Firm=1*)		
Spec_Education	**Margin**	**St. Err.**	**Sig**	**Margin**	**St. Err.**	**Sig**
0	0.421	0.005	***	0.448	0.023	***
0.5	0.398	0.006	***	0.459	0.036	***
1	0.377	0.010	***	0.471	0.055	***
1.5	0.355	0.013	***	0.482	0.075	***
2	0.334	0.017	***	0.494	0.096	***
2.5	0.314	0.020	***	0.505	0.117	***
3	0.294	0.024	***	0.517	0.138	***
3.5	0.274	0.027	***	0.528	0.159	***
4	0.256	0.029	***	0.540	0.179	***
4.5	0.238	0.032	***	0.551	0.200	***
5	0.221	0.034	***	0.563	0.220	***
5.5	0.204	0.035	***	0.574	0.240	***
6	0.188	0.037	***	0.586	0.260	***
6.5	0.173	0.038	***	0.597	0.279	***
7	0.159	0.038	***	0.608	0.298	***
7.5	0.146	0.039	***	0.619	0.316	***
8	0.133	0.039	***	0.630	0.334	***

	Teammates with competencies No common ground (*D_Others_SE=1*, *D_Same_Firm=0*)			Teammates without competencies Presence of common ground (*D_Others_SE=1*, *D_Same_Firm=1*)		
Spec_Education	**Margin**	**St. Err.**	**Sig**	**Margin**	**St. Err.**	**Sig**
0	0.275	0.012	***	0.317	0.071	***
0.5	0.273	0.011	***	0.319	0.069	***
1	0.271	0.011	***	0.320	0.066	***
1.5	0.269	0.012	***	0.322	0.063	***
2	0.266	0.012	***	0.323	0.060	***
2.5	0.264	0.013	***	0.324	0.057	***
3	0.262	0.014	***	0.326	0.055	***
3.5	0.260	0.016	***	0.327	0.052	***
4	0.258	0.017	***	0.329	0.049	***
4.5	0.256	0.018	***	0.330	0.046	***
5	0.254	0.020	***	0.331	0.044	***
5.5	0.251	0.021	***	0.333	0.041	***
6	0.249	0.023	***	0.334	0.038	***
6.5	0.247	0.024	***	0.336	0.036	***
7	0.245	0.026	***	0.337	0.033	***
7.5	0.243	0.027	***	0.338	0.030	***
8	0.241	0.029	***	0.340	0.028	***