ENTREPRENEURIAL TEAMS' HUMAN CAPITAL: FROM ITS FORMATION TO ITS IMPACT ON THE PERFORMANCE OF TECHNOLOGICAL NEW VENTURES

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DISCLAIMER

This research uses data from the Census Bureau's Longitudinal Employer Household Dynamics Program. Any opinions and conclusions expressed herein are those of the author(s) and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed.

ABSTRACT

Startups' human capital, especially founding teams' pre-entry experience, has long been studied as a determinant of their performance. However, little is known on the complementarities between the different pre-entry experiences and on the influence of these pre-entry experiences on startups' performance and on startups' acquisition of new human capital. My dissertation fills this gap with two essays. In my first essay, I show that two types of pre-entry experiences, target industry experience and experience outside the target industry, are complementary when one is shared across the founding team members and the other is embodied within team members who worked in multiple firms. In my second essay, I show that pre-entry experience makes potential hires more attractive to startups. However, startups appear more attractive to these potential hires if they can signal productivity and growth potential rather than prior experiences. I also find that gender affects the selection of the potential hires and their earnings suggesting the existence of disparities in the startup environment. By using interactions between different experiences, in and outside the target industry, and between different levels of analysis, the team and the individuals, my dissertation enriches our understanding of startups' human capital and its effects on performance and acquisition of talent.

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CHAPTER 1
INTRODUCTION

Startups are major vehicles of economic growth – they contribute to discovery of inventions, commercialization of new products and creation of jobs (Wennekers & Thurik, 1999). Even though some startups become successful, their survival during their first years is often precarious because they have to overcome lack of legitimacy and face competition from established firms (Freeman, Carroll, & Hannan, 1983; Singh, Tucker, & House, 1986). Often, the only resource they have to compete early on is the human capital residing in their founders and first employees. Part of this human capital was developed prior to the establishment of the startup and mainly resides in the knowledge acquired from prior experiences (Colombo & Grilli, 2005; Helfat & Lieberman, 2002; Klepper, 2002). The pre-entry experience is thus what constitutes their first resources and what helps them build or acquire more resources, which in turn affects their startup performance (Delmar & Shane, 2006; Shane & Stuart, 2002).

Founding team members' pre-founding experience can vary. Founding team members might have all worked in the same incumbent firm and left to create their startups such as the founders of Intel who left Fairchild to create their startup (Holbrook, Cohen, Hounshell, & Klepper, 2000). They might have worked in different places and been connected by other kinds of relationships such as kinship (Ruef, Aldrich, & Carter, 2003; Wasserman, 2012). Their shared or diverse experience, in combination to the source of the experience in the startup industry or in other industries, will affect the trajectory of their startup. Further, startup human capital is likely to evolve – some team members are likely to leave while new individuals are brought in (Ucbasaran, Lockett, Wright, & Westhead, 2003). The initial pre-entry experience of the founders is also likely to affect who is hired as well as the characteristics of the individuals who join (Beckman & Burton, 2008; Ucbasaran et al., 2003).

Prior research has exemplified the effect on startup performance of one type of pre-entry experiences – the experience acquired in the target industry (i.e. in the industry of the startups) (Agarwal, Echambadi, Franco, & Sarkar, 2004; Chatterji, 2009; Delmar & Shane, 2006; Eisenhardt & Schoohoven, 1990; Franco & Filson, 2006; Klepper, 2002; Roberts, Klepper, & Hayward, 2011). While this stream of work sheds light on an important type of prior experience, it rarely examines whether other experiences could also be beneficial to the startups (Colombo & Grilli, 2005; Eisenhardt and Schoohoven, 1990) and complementary to the target industry experience.

This gap leads to two overarching questions. The first question concerns the existence of complementarities between target industry experience and other prior experiences. What are the other types of prior experience and how can these other types of experience be of use and turn out complementary for startups with target industry experience? The second question concerns the development of the human capital in the startups. How would this endowment of target industry experience help startups attract more human capital by hiring talented employees? The flip side of the question concerns startups that do not possess such endowment. How can they build it and attract employees with target industry experience? Answering these two questions expands our understanding of the heterogeneity in startup performance and in acquisition of human capital.

At the intersection of these questions also reside the interactions between founding teams and individuals. These individuals can already be part of the founding team at the initial stage or aspire to be part of the startup at a later stage. This second layer of analysis allows us to better understand how experience complementarities or search for complementarities play out. Answering these questions also informs the major actors of the startup environment such as the startup founders, their early employees and policy makers.

My dissertation answers these two fundamental questions in two essays. In the first essay, I exploit two dimensions of pre-entry experience: the content, in the target industry experience or outside, and the scope, residing in the team or in individuals. Regarding the latter dimension, I examine how team members who embody diverse experience can be the source of the complementarities of experiences that other types of teammates are not able to offer. I call these team members job hoppers as by definition, they had multiple jobs. Job hoppers represent a phenomenon that was mentioned for one of the first times in management in the 1950s (Culley & Slavick, 1959) and refers to individuals who change jobs often, without a clear definition of the frequencies or of the reason for changing jobs. In this dissertation, job hoppers are defined as individuals who decide to change jobs to pursue a new opportunity (Malone, 1995) and not because of bad performance. While their employer might fear their next move, they are also a vector of knowledge spillovers from which employers and even industrial clusters benefit (Saxenian, 1996). Thanks to their hopping, they are able to gather a unique set of knowledge based on multiple and recent moves.

I find that the inclusion of job hoppers benefits startups whose founding teams have prior shared experience. Startup performance is positively associated with the interaction of prior shared experience and job hoppers when the prior shared experience is of at least three years. In addition to be contingent on the length of the prior shared experience, these complementarities are contingent on the source of experience. I find that startups with prior shared experience in target industry benefit from job hoppers who worked outside the target industry. I also find that startups with prior shared experience outside the target industry benefit from job hoppers who worked in the target industry. These two effects are positive when the respective prior shared experiences are of two years or more. This essay uncovers a specific type of complementarities that underlies the positive effect of experience diversity.

In the second essay, individuals called joiners are the key level of analysis with the startup founding teams. Joiners are a defined set of individuals who are hired in a given labor market (i.e. year, industry and state market) by startups in their early stages. The term of joiners comes from Roach and Sauermann (2015): joiners are "*individuals who are attracted to working in startups as employees but who do not want to be founders themselves.*" Their characteristics, such as experience, ability and demographics, affect how attractive a startup sees them.

In this second essay, I explore how target industry experience alongside with other characteristics influence startups' and joiners' decision to work together. I use a two-sided matching model methodology that reveals which characteristics make each side an attractive counterpart for the other and operationalizes hiring as a mutual selection decision (Chen, 2013; Park, 2013; Sørensen, 2007). I find that startups that can signal productivity and growth potential through founding teams’ education and size are more attractive employers. I do not find that startups’ target industry experience affects the mutual selection. This is an important finding because it suggests that startups that do not possess pre-entry knowledge of the industry can attract joiners with that experience. On the joiner side, their target industry experience is a key characteristic. I also find that male joiners are preferred. This is an important finding that can fuel the debate on sexism in technological industries and in startups (Khazan, 2015). I also examine the performance of the joiners, measured by earnings one year after they were hired, and found that it is mainly explained by their ability, the ability of the founding team, and their gender and race. This shows that when controlling for ability, the experience effect on individual performance is not significant. This result also suggests that earnings structure is carried over from established firms to startups and that disparities based on gender and race exists in startups.

The two essays examine how the initial human capital endowment of startups affects survival and the acquisition of more human capital through hiring. The first essay suggests that startup with shared target industry experience can even perform better when they include job hoppers with experience from outside the target industry. The second essay shows that target industry experience positively influences the probability of a joiner to be preferred by a startup over his or her competitors. However, the target industry experience of the startups does not provide them with any hiring advantage. In other words, it does not give them access to better potential hires. In that sense, both essays complement each other and offer a more nuanced view of the spinouts. Further, the second essay relates to the discussion of team formation of the first essay by explicitly modeling team member additions.

In conclusion, my dissertation examines how startups' initial experience endowment affects their performance and, subsequently, their acquisition of experience via hiring. The resource endowment revolves around target industry experience, which has been long shown as a crucial initial resource. However, to expand current research, my dissertation examines the interaction between target industry experience and experiences acquired in other industries in the first essay, as well as signaling of productivity and growth potential in the second essay. These interactions play out across two levels of analysis, that of the initial founding team, and that of the individual team member. The connection between both levels enriches the understanding of the effect of stock of experience and its evolution. This entire framework provides a unique insight into startups' human capital.

CHAPTER 2
LITERATURE REVIEW

In this literature review, I define the key unit of analysis of my dissertation, the entrepreneurial team. I then summarize the findings on the relationship between entrepreneurial team's prior work experience (hereafter, experience) and startup performance. Relevant to the relationship is the categorization entrepreneurial teams' experience along two dimensions: the content as it pertains to prior industry experience (hereafter, industry experience), and the scope of the experience in the team as it pertains to prior shared experience versus diverse experience. Further, I summarize the findings on the relationship between entrepreneurial team's experience and entrepreneurial team's acquisition of talent. This relationship is put into perspective with the two other main mechanisms, homophily and interpersonal attraction, which affect team formation and acquisition of talent. For each body of work, I highlight the areas of expansion covered by my dissertation.

Teams of entrepreneurs are responsible for the creation of eighty-five percent of new companies in technological industries (Wasserman, 2012). As these teams strongly influence development and performance of their startups, they are under researchers' and policy makers' scrutiny. To understand their influence, it is first important to define them. These founding teams are voluntarily formed teams of people who start a new venture in which they take part as managers or employees (Cooney, 2005). Some scholars use equity holding in the venture as a criterion to determine the members of the entrepreneurial team (Kamm & Nurick, 1993; Ruef et al., 2003). This dissertation relies on a more inclusive definition because relying solely on stock ownership would exclude from the analysis a fraction of the initial employees who have a consequential and long-lasting influence on the new venture's strategies, strategy implementation, and performance (Stinchombe, 1965; Boeker, 1988; Eisenhardt & Schoonhoven, 1990; Baron, Hannan, & Burton, 1999; Beckman & Burton, 2008).

ENTREPRENEURIAL TEAM'S EXPERIENCE AND STARTUP PERFORMANCE

Industry experience

When entrepreneurs join forces to create a startup, they bring their prior work experience and associated knowledge to the table. This experience should enable them to seize opportunities, to avoid mistakes, and to perform well (Delmar & Shane, 2006). Prior research has often investigated the role of industry experience, the experience acquired in the industry in which the startup is created. For instance, Delmar and Shane (2005) argued that industry experience provides the team with knowledge about how to exploit business opportunities, how to serve the customers, and how to access important suppliers and distributors. They showed that industry experience has a positive effect on startup survival and sales growth.

Delving into the industry knowledge, a whole stream of entrepreneurship literature has studied spinouts. Spinouts are independent new ventures created by employees of industry incumbents and thus, by definition, their founding teams have industry experience (Garvin, 1983; Agarwal et al., 2004; Franco & Filson, 2006). This research stream first has examined how parent firm knowledge affects the decision of employees to spin out (Agarwal et al., 2004, Klepper & Sleeper, 2005; Gambardella, Ganco & Honoré, 2014). It has also showed that spinouts perform better than other types of new ventures whose teams have knowledge of other industries (Agarwal et al., 2004;

Chatterji, 2009; Roberts, Klepper, & Hayward, 2011). This industry knowledge can relate to the technologies, market, or regulations of the industry (Agarwal et al., 2004; Slepper & Klepper, 2005; Chatterji, 2009). For instance, the transfer of technological knowledge was found to increase the survival of spinouts in the disk drive industry (Agarwal et al., 2004) whereas the transfer of regulatory knowledge gets spinouts faster funding (Chatterji, 2009).

Prior shared experience

While many studies call startups spinouts if one of the team member came an incumbent firm from the industry of the startup (Simons, 2005), most startups have multiple team members coming from the same incumbent (Holbrook et al., 2000; Ganco, 2013). These team members, by working in the same incumbent firm at the same time, build prior shared experience.

Prior shared experience is found to have a positive impact on startup performance (Kor, 2003; Roure & Keeley, 1990; Zheng, 2012). In the incumbent firm, team members who worked in the same incumbent firm typically acquired the same organizational knowledge, such as processes and routines. Then, they can use these routines and processes in their startup and build an organizational advantage over other new ventures (Eisenhardt & Schoonhoven, 1990; Philips, 2002; Beckman, 2006; Agarwal, Campbell, Franco, & Ganco, 2013). In addition, these team members also had the opportunity to learn through direct observation or hearsay of each other's capacity (Katz, 1982; Reagans, Argote, & Brooks, 2005; Muendler & Rauch, 2012). This learning limits information asymmetry among team members and permits a better organization of the work in the team (Reagans et al., 2005).

Diverse experience

Prior research has also examined the effect of entrepreneurial team's diverse experience, but to a limited extent[1]. Regarding diverse experience defined as experience acquired in various industries, one of the first studies of entrepreneurial teams (Eisenhardt & Schoonhoven, 1990) showed that the standard deviation of teams' industry experience has a positive effect on performance. This indirectly suggests that team members with no experience or, most likely, team members with experience in other industries are beneficial for the startup. On the other hand, Colombo and Grilli (2005) found a negligible effect of other industry experience on startup performance. Regarding diverse experience defined as experience acquired in various firms, Beckman (2006) found that team members who worked in the same firms as well as in different firms prior to creating their startup perform better. Further, in the contexts of spinoffs, startups created by parent firms that maintain a connection with the ventures, research shows that spinoffs whose knowledge partially overlaps with their parent firm perform better than startups whose knowledge completely overlaps or not at all (Sapienza, Parhankangas, & Autio, 2004). This suggests that knowledge from other firms than the parent firm is beneficial.

Areas of expansion

Because spinout and entrepreneurial team literatures have focused on the effect of target industry experience on performance, there is a clear opportunity to study the effect on performance of the experience acquired outside the parent firm or outside the target

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[1] Note that a lot of the work on entrepreneurial team diversity has focused on functional background diversity (Beckman, Burton, O'Reilley, 2007; Beckman & Burton, 2008) or demographic diversity (Chowdhury, 2005; Steffens, Terjesen & Davidsson, 2012).

industry. Second, when diverse experience has been studied, the results have not been conclusive. It is unclear whether the diverse experience brought by a handful of team members would be beneficial to the startup performance as opposed to by the whole team. It is also unclear whether the diverse experience acquired in a different industry and/or in multiple firms would be beneficial. My dissertation fills these gaps by examining the effect of the interaction between team's prior shared experience and team members who individually embody diverse experience. This diverse experience is acquired across firms in the target industry or across firms in one or several different industries. My dissertation thus highlights one specific mechanism underlying the complementarities between different kinds of experiences that a founding team can include.

ENTREPRENEURIAL TEAM EXPERIENCE AND ACQUISITION OF TALENT

The entrepreneurship literature has almost exclusively focused on entrepreneurs and their entrepreneurial team; however, some attention began to be drawn to the joiners. Joiners are defined as people who join startups in the first few years of the startup existence. These joiners do not bear as much risk as the entrepreneurs but still enjoy similar characteristics such as more work independence. In a sample of engineer and PhD students, Roach and Sauerman (2015) found that both entrepreneurs-to-be and joiners-to-be have some pre-entrepreneurial orientation. However, entrepreneurs-to-be have stronger preferences for autonomy, risk and commercialization than do joiners. The students who wish to become entrepreneurs are influenced by their own characteristics while the ones who would like to join a startup are also influenced by contextual factors.

The next logical step is to investigate how joiners and startups select each other. Insight on this pairing-up can be drawn from prior work on entrepreneurial team formation, which treats both the initial formation and the subsequent member addition. Even when these two stages are combined, the literature is scarce, probably because it is difficult to observe the phenomenon. Despite the difficulties, three main mechanisms have been identified: resource seeking (Forbes et al., 2006); homophily (Ruef et al., 2003); and interpersonal attraction (Forbes et al., 2006). The latter two are discussed together because they both rest on individuals' preferences. Some scholars also use a network perspective to inform team formation (Aldrich & Kim, 2007). However, the use of a network is not, strictly speaking, a mechanism of team formation, but rather a mechanism to identify the pool of potential teammates and is not treated in this dissertation.

Resource seeking behavior

Resource seeking behavior is the tendency of people to associate with those who have the resources needed to realize a task. In an entrepreneurial team, one could expect each founder to bring resources the others lack, for instance, human capital and social capital (Forbes et al., 2006).

Researchers found mixed support for the resource seeking behavior, which is not often the main factor of selection but a factor alongside homophily. In their foundational paper, Kam and Nurick (1993) discussed the importance of diversity of skills and alignment of incentives but did not bring evidence of these. In Cruz and colleagues' context of family businesses, resources such as human, technological, and external social capitals were only considered in determining roles in the venture but not the initial formation. With a sample representative of the US economy, Ruef and colleagues (2003), who called this behavior functionality, did not find any empirical support for this.

In the context of team evolution and team member addition, Clarysse and Moray (2004) studied the evolution of an academic spinoff and found that the core of the team was made up of the three researchers who initiated the project. Rapidly, three other people joined, mostly to fill technical needs (Clarysse & Moray, 2004). Later on, the team incorporated an external business coach. Little is said about the selection of additional teammates. The technology transfer office of the university could have helped the three initial researchers to find teammates. The researchers mentioned that a compatible personality was one of the criteria of selection besides needed technical skills. Also, in the context of academic spinoffs, Forbes et al. reported, based on their interviews, that both interpersonal attraction and resource seeking influenced member addition (2006). Based on a survey of 92 ventures in Great Britain, Ucbasaran and colleagues found that member addition is pursued to bring more human capital to the team, while the exit of team members is most often due to emotional reasons (Ucbasaran et al., 2003). Overall, experience as a resource sought in the mutual selection does not stand out as the main driver of mutual selection.

Homophily and interpersonal attraction

Homophily is the tendency of people to like people similar to them and, thus, to work with them. While homophily was already identified by the ancient Greek philosophers, sociologists started using it as a central focus in the 1920s and 1930s (Freeman, 1996; McPherson, Smith-Lovin, & Cook, 1987). Homophily can be chosen – when people are presented to a heterogeneous group of people, they choose to associate with the people similar to them (McPherson, Smith-Lovin, & Cook, 2001). Homophily can be induced – when people tend to live or work with people already similar to them, they can only associate with similar people. People can associate based on status homophily where they would seek similarity regarding demographic characteristics such as age, education, religion and current behavior (Lazarsfeld & Merton, 1954). Note that these demographic characteristics can be ascribed (such as age) or chosen (such as education). People can also associate based on value homophily where people seek out other people with similar values, beliefs, and attitudes towards future behaviors (Lazarsfeld & Merton, 1954).

In the entrepreneurship literature, Ruef and colleagues (2003) found in the Panel Study of Entrepreneurial Dynamics (PSED) that founders tend to team up with teammates of the same gender, race, and occupation, which illustrates status homophily. In their multi-case analysis of family businesses in Honduras, Discua Cruz and colleagues found that the mutual selections of teammates among family members were based on shared commitment, values, and trustworthiness (Discua Cruz, Howorth, & Hamilton, 2012), which illustrates value homophily. None of these studies determine whether the homophily was chosen or induced.

Other studies explain team formation based on interpersonal attraction. While this concept is different from homophily, most research ends up treating interpersonal attraction based on similarities. The connection between these two concepts seems therefore logical. Starting a venture often is compared to getting married – it is all about finding the right partner. Some entrepreneurs even described the phenomenon as chemistry playing out between them and their business partners (Kamm & Nurick, 1993).

Forbes and colleagues (2006) in the context of academic spinoffs, found that interpersonal attraction was crucial for a new teammate to enter the team. They also realized that this attraction was based on sharing similar values or characteristics (Forbes et al., 2006).

Joiners' earnings

In addition to team member's decision to be part of an entrepreneurial team, prior research also studied their individual performance in terms of earnings. For instance, in the semi-conductor industry, a few years after their entrepreneurial experience, entrepreneurs receive higher earnings than their colleagues who remain employed by incumbent firms (Campbell, 2013). While this could be due to the acquisition of human capital during the entrepreneurial experience (Campbell, 2013), it could also result from higher ability of the individuals who select entrepreneurship at a point where they can fully exploit an entrepreneurial opportunity (Braguinsky, Klepper, & Ohyama, 2012). Concerning the joiners, little is known on their earnings and on how the mutual selection between startups and joiners affect their earnings.

Areas of expansion

The literature on entrepreneurial team formation can inform the hiring by startups. However, it has some limitations. First, by definition, it is focused on the initial stage of team development. Therefore, the results might be different from when the startups are incorporated, employ the founders, and are hiring. Second, the difficulty of studying the phenomenon of team formation might have impacted the methodology used and probably the findings that mainly highlight the role of homophily. The first group of studies was qualitative and relied on interviews and case studies in very specific contexts such as family businesses and academic startups where firms might not consider a large pool of potential hires. By definition, family businesses and academic spinoffs focus on family members and technology transfer office connections, respectively. The second group of studies used samples representative of the US and UK economies (Ruef et al., 2003; Ucbasaran et al., 2003), which include businesses for which prior experience might not be as critical. As the context in which the entrepreneurs evolve influences the team formation (Aldrich & Kim, 2007), it is likely that studying other contexts, including technology or growth-driven contexts will make resource-seeking behavior and prior experience more salient.

The second essay of my dissertation fills this gap by investigating the mutual selection between startups and joiners in technological industries. I explain this mutual selection based on startups' and joiners' characteristics that reflect resource-seeking behavior as it relates to prior experiences and knowledge, homophily as it relates to demographic characteristics, and signals of productivity, ability and growth potential as they relate to performance maximization. Further, my dissertation also shows which joiners and startups characteristics affect joiners' future earnings once the effect of these same characteristics on mutual selection has been taken into account.

CHAPTER 3
ESSAY 1
FROM COMMON GROUND TO BREAKING NEW GROUND: FOUNDING TEAMS' PRIOR SHARED EXPERIENCE AND STARTUP PERFORMANCE

INTRODUCTION

Entrepreneurs often create new ventures with their colleagues. The founding team members therefore share prior work experience (Holbrook et al., 2000; Ganco, 2013). This prior shared experience is positively associated with startup performance because it provides founding teams with common organizational knowledge and routines (Philips, 2002; Agarwal et al., 2013) and insights on each team member’s strengths and weaknesses (Lange, 2007; Muendler & Rauch, 2012). If the prior shared experience occurred in the industry of the future startup, it also provides knowledge on the relevant technology, market and regulations (Agarwal et al., 2004; Klepper & Sleeper, 2005; Chatterji, 2009). These findings suggest that founding teams with prior shared experience in the target industry should create startups that outperform others.

While prior studies on startups have highlighted the positive effect on performance of prior shared experience (Kor, 2003; Roure & Keeley, 1990; Zheng, 2012) and the positive effect of target industry experience (Agarwal et al., 2004; Chatterji, 2009), little is known on the effect of experiences acquired outside the common prior employer or outside the target industry. Further, the heterogeneity among firms with prior shared experience is not fully explained either. For instance, startups whose knowledge is not entirely coming from the target industry or from the same parent firm perform better (Eisenhardt & Schoonhoven, 1990; Sapienza et al., 2004). However, this does not explain where the rest of the knowledge is coming from, or what complementarities might exist between different sources of knowledge. In technological industries where innovation even in niche markets is a key driver of survival (Agarwal, 1998; Klepper & Simons, 2000), knowledge from different sources that can be recombined into innovation is likely to be an asset.

To outperform their competitors, startups need a founding team that not only extensively shares knowledge but also incorporates knowledge with unique elements. Second, deep knowledge of the industry the team enters is needed to compete but may also limit its potential for innovation. The founding team thus needs a combination of target industry knowledge and knowledge about other industries. To solve this puzzle, founding teams may include individuals who can complement the shared knowledge with diverse knowledge. In other words, these individuals would embody the diverse experience. I call these individuals job hoppers because they, by definition, embody diverse experience by having worked in multiple firms over a recent period of time. I examine the effect of job hoppers because they provide diversity of experience as opposed to team members who had one long experience in only one organization. They can thus be both disruptive and innovative. Further, job hoppers also synthesize the knowledge they acquired across multiple experiences and, thus, the costs of knowledge integration are lower than if each teammate were to bring knowledge from one of these experiences. Based on the observable choices founding teams make, I investigate the effect on startup performance of the complementarities between job hoppers and the prior shared experience.

Job hoppers are workers who change jobs frequently. They were mentioned for one of the first times in management in the 1950s (Culley & Slavick, 1959). There is no established frequency to be called a job hopper but, typically, job hoppers[2] switch to a new job as soon as an interesting opportunity occurs and do not build careers in one company (Malone, 1995). In areas where the density of firms in the same or related industries is high, job hoppers are often considered responsible for knowledge spillovers (Saxenian, 1996; Fallick, Fleischman, & Rebitzer, 2006). Established firms tend to offer job hoppers higher wages (Mithas & Krishnan, 2008), which suggests that they value their multiple experiences. However, in cases of departure they are costly to firms (Mitchell, Holtom, & Lee, 2001). In the entrepreneurial domain, job hoppers who become entrepreneurs have more innovative startups that are less likely to fail although they undergo early difficulties in getting funding (Wu & Dokko, 2008). They can also be actors of technological or organizational change as they synthesize knowledge accumulated across various experiences (Taylor & Greve, 2006; Wu & Dokko, 2008).

To study the moderating effect of job hoppers, I first establish a baseline relationship – the effect of a team's prior shared experience on the startup performance. Controlling for the job hoppers' quality and based on their diverse experience, I then argue that job hoppers can disrupt the shared knowledge and bring knowledge different from the shared one to help startups to innovate. I thus posit that job hoppers positively moderate the relationship between prior shared experience and performance. I also examine whether the effect of job hoppers is contingent on the types of prior shared experiences and their own past experience. Specifically, when job hoppers disrupt the team's shared knowledge, they have to come up with an innovative replacement using knowledge new to the rest of the team. Thus, I expect that teams with target industry

[2] In this paper, I refer to job hoppers as those who change jobs at their will and not because of poor performance.

knowledge benefit more from job hoppers who primarily worked outside the target industry while teams with knowledge about an industry other than the target industry benefit more from job hoppers who primarily worked in the target industry.

I test this theoretical framework with the employee-employer linked dataset provided by the US Census Bureau (LEHD). The study focuses on the entire population of new ventures created by at least two people in five technological industries between 2000 and 2006 in 18 US states. As the LEHD coverage is from 1991 to 2008, I am able to build precise measures of experience prior to the startup creation and of survival for several years after the startup creation. Pervasive to the literature on founding teams and performance is the issue of the unobserved selection of the team members and how their unobserved intrinsic quality could bias the results (Eesley, Hsu, & Roberts, 2013). To tackle this issue, I include strong control variables that proxy for quality of the startup opportunities and quality of the team members based on the past and current earnings of the founding team.

To foreshadow my results, I find that a founding team's prior shared experience is positively related to startup performance, measured by survival. I also find that the inclusion of job hoppers in these teams positively moderates the relationship. As for the contingent effect of job hoppers, I find that the job hoppers who worked outside the target industry positively moderate the effect on survival of prior shared experience within the target industry. I also find that the job hoppers who worked inside the target industry positively moderate the effect on survival of prior shared experience outside the target industry. These results, as well as the robustness checks I developed, suggest that there should indeed be two mechanisms underlying the effect of job hoppers: disrupting inherited and redundant knowledge; and innovating by bringing diverse knowledge.

With these results, the paper shows that prior shared experience in combination with the inclusion of job hoppers leads to longer survival. This is an important finding in that it shows that knowledge diversity across the entire founding team is not necessary, nor always beneficial. By contrast, a combination of similar knowledge shared by all or most of the team and diverse knowledge embodied in one or a few team members turns out to be beneficial for startup survival. Further, by showing the complementarities between prior shared knowledge of the industry the startup enters and job hoppers' knowledge of other industries, the paper explains some of the performance heterogeneity of spinouts. Practically, the paper suggests that entrepreneurs who work with co-founders with whom they share knowledge and co-founders who bring knowledge diversity would be associated with longer survival.

THEORY AND HYPOTHESES

Founding teams refer to voluntarily formed teams of people who start a new venture in which they take part as managers or employees (Cooney, 2005). This paper relies on a more inclusive definition than stock ownership for two reasons. As new ventures have smaller numbers of employees and fewer hierarchical levels than established firms, the initial employees' prior experience and knowledge have a consequential influence on the new venture's strategies, strategy implementation, and performance. Further, the influence of these early employees has long lasting effects on the startup life course (Stinchombe, 1965; Boeker, 1988; Eisenhardt & Schoonhoven, 1990; Baron et al., 1999; Beckman & Burton, 2008).

The founding teams' influence is due to their early decisions and actions that are based on the team members' previous experience and associated knowledge. If the team members were previously colleagues, this experience is similar and tends to have a positive impact on startup performance for several reasons. First, when these individuals worked for the same incumbent firm prior to the startup, they typically acquired some of the same organizational knowledge, such as processes and routines. Later, after becoming entrepreneurs, they can use these routines in their startup, providing them with an organizational advantage compared to other new ventures (Eisenhardt & Schoonhoven, 1990; Philips, 2002; Beckman, 2006; Agarwal et al., 2013). In addition, if the team members worked for the same incumbent firm at the same time, they also had the opportunity to learn through direct observation or hearsay each other's strengths and weaknesses (Katz, 1982; Reagans et al., 2005; Muendler and Rauch, 2012). These processes of insight gathering build up over time (Lange, 2007; Muendler & Rauch, 2012). The longer the shared experience, the more realistic the team members' expectations of each other and the stronger their adaptation becomes. This, in turn, creates a better work outcome (Gilson, Mathieu, Shalley, & Ruddy, 2005; Taylor & Greve, 2006) and higher startup performance. To summarize, because prior shared experience provides a common organizational framework for the team, startups led by founding teams with shared experience are expected to perform better than startups led by founding teams without shared experience.

In addition to organizational knowledge, if the founding team's startup enters the industry in which the team worked previously, the team also benefits from additional industry-specific knowledge. This industry-specific knowledge can relate to the technologies, market, or regulations of the industry (Agarwal et al., 2004; Slepper and Klepper, 2005; Chatterji, 2009) and has a positive effect on firm performance (Delmar and Shane, 2006; Roberts et al., 2011). For instance, the transfer of technological knowledge was found to increase the survival of spinouts in the disk drive industry (Agarwal et al., 2004) whereas the transfer of regulatory knowledge gets faster funding for spinouts (Chatterji, 2009).

In summary, previous research highlighted that entrepreneurs who worked together in an incumbent firm prior to founding their startup accumulated different kinds of knowledge that increases their startup performance. Thus, I posit as a baseline hypothesis that:

Hypothesis 1: A founding team's prior shared experience increases startup performance.

Although this hypothesis is well established in the literature, there are reasons to believe that experience that is not shared by most of the team can be beneficial as well. First, this different experience can be useful to question the inherited organizational knowledge. If the founding teams share extensive organizational knowledge from their prior experience, they are more likely to reproduce and use the same organizational features, such as routines, in the startup (Philips, 2002). The team members might be committed to these routines regardless of their intrinsic quality (Levitt & March, 1988).

Second, this different experience can be useful to explore and innovate (Beckman, 2006). Teams with prior shared experiences have also inherited technological knowledge from their parent firm (Agarwal et al., 2004; Sleeper & Klepper, 2005). The opportunity exploited in their startup also often comes from their previous work at the parent firm (Bhide, 1994; Gambardella et al., 2014). This heritage provides the team with a more developed business opportunity than other teams but can limit their innovation. In technological industries, simple replication of a previously acquired idea could have harmful consequences. The parent firm can simply sue the startup or the startup can be stuck with outdated products. In all these cases, this would lead to the failure of the new venture.

Prior studies have mostly shown that team diversity in terms of prior experiences has a positive effect on performance (Beckman, 2006). The question that emerges, though, is where the diverse experience would be coming from when most of the team shares the same prior experience which is often the case in the startup context (Holbrook et al., 2000; Ruef et al., 2003; Wasserman, 2008). Connected to this question is the search for the complementarities that underlie the fact that *some experience diversity* is beneficial for startup performance. To explore this topic, this paper focuses on the inclusion in the teams of individuals who had recent multiple work experiences, the so-called job hoppers and can bring knowledge from multiple sources to teams that share the same knowledge.

Complementary effect of job hoppers in teams with prior shared experience

Job hoppers are individuals who change jobs as soon as they identify a new opportunity and so build a "unique" stream of experiences. This unique stream of experience should be beneficial to startups and should be likely to be incorporated by the rest of the team (Shulz, 2006; Fern, Cardinal, & O'Neill, 2012). However, job hoppers are not always well perceived as their commitment to an organization can be low and their contribution might also be contingent on the type of team in which they work. When job hoppers are part of teams with shared experience, they represent a minority and their contribution can be accepted under several conditions. Prior work on the influence of minorities has shown that minority newcomers influence groups when the tasks of the group are complex and when the decision making is shared among group members (Choi & Levine, 2004; De Dreu & West, 2001). As founding teams are voluntarily formed and because launching a startup is a complex task, one can reasonably think that job hoppers will influence the startup organization and its activities. Therefore, when they are included into teams with shared experiences, their contribution is likely to be beneficial and plays out through two mechanisms.

First, because of their frequent change of employers, job hoppers have to adapt to various organizations and their respective routines. Having worked with a broader range of routines than a non-hopping worker, they are more critical of their new firm's organizational processes and routines and are likely to disrupt them. This ability to be critical and thus play the role of devil's advocate should influence the decisions of the team (Schwenk, 1990). Further, the opinion of team members with a unique experience or stream of experiences is more likely to have an impact on the team's decisions than the opinion of an ordinary team member (Fern et al, 2012). The rest of the team is, thus, more likely to pay attention to the critics and be willing to change the routines. Thus, the presence of job hoppers on the team offers the team an opportunity to learn from other organizations and increases the possibility of constructively disrupting the inherited organizational processes and reducing inertia.

Second, given that innovation is mainly built on the recombination of existing knowledge (Katila & Ahuja, 2002; Fleming & Sorenson, 2001; Schilling & Green, 2011), job hoppers who collected a broad range of knowledge from multiple past work experiences are in a position to be innovative. After all, individuals have more possibilities to combine the knowledge they have acquired in previous experiences than teams that may draw on a broader scope of knowledge, the coordination costs of which are tremendous (Taylor & Greve, 2006; De Dreu & West, 2001). The inclusion of job hoppers, then, increases the team's knowledge and innovation potential. This inclusion is useful for teams who share extensive knowledge and may lack the knowledge diversity that can create innovation.

Thus, I expect the job hoppers to have a dual role in the founding team: disrupting inert knowledge; and bringing knowledge for potential innovations, which in turn has a positive effect on the relationship between a founding team's prior shared experience and performance.

Hypothesis 2: The inclusion of job hoppers on the founding team positively moderates the effect of prior shared experience on startup performance.

While job hoppers may contribute to constructive disruption and innovation in the startup, the full or partial success of these contributions might be contingent on the team's prior shared experience and their individual prior experience. Because founding teams with experience in the target industry have better performing startups (Argawal et al., 2004; Chatterji, 2009), it makes sense to split the founding teams' prior experience this distinction. I thus split the shared experience into two categories: shared experience in the target industry; and shared experience outside the target industry. I also split the job hoppers into two mutually exclusive groups according to the job hoppers' prior industry experience. The first group is the group of job hoppers who primarily worked outside the target industry (i.e. outside job hoppers), and the second one is the group of job hoppers who primarily worked inside the target industry (i.e. inside job hoppers). Primarily means that the number of jobs in one category exceeds the number of jobs in the other category. In case of a tie, the most recent job experience prevails.

Complementary effect of job hoppers in teams with prior shared experience within the target industry

In a team with prior shared experience in the target industry, the team members share routines that are already adapted to the target industry (Philips, 2002). The team can be overcommitted to these routines that worked in the past but might not be optimal for the startup (Levitt & March, 1988; Baum & Ingram, 1998). The team members also share specific knowledge, such as technological knowledge, that is already applied in the industry by incumbents (Sleeper & Klepper, 2005). While this knowledge is customized for the industry, the scope of the shared knowledge is narrow, which limits the recombination possibilities and the startup innovation (Fleming & Sorenson, 2001; Katila & Ahuja, 2002).

When job hoppers are part of the founding team, they can disrupt the inherited routines and knowledge. When these routines and technological knowledge are disrupted, they have to be replaced so that the new ones become more efficient or innovative. In the case of routines and knowledge already embedded and accepted in the target industry, the disruption and innovation of these routines and knowledge should come from their combination with the ones coming from other industries.

In the context of manufacturing industries, firms often incorporate technologies that have been developed in other industries. The most obvious examples include the incorporation of software and of lighter materials in a wide range of manufacturing industries from vehicles manufacturing to electronic devices. At the new venture level, founding teams can also incorporate knowledge coming from various industries. For instance, consider the case of Icon Aircraft, a designer and manufacturer of light sport aircrafts that can be folded, carried and flown easily. Icon's engineering team primarily came from Scaled Composite, another aircraft designer and manufacturer. However, one of the team leaders, Steen Strand, came from the consumer goods industry where he developed designs for skateboard and healthcare products. Steen Strand was able to bring to the engineering team a different perspective and design ideas that helped Icon products meet their goals of being easy-to-fly and affordable. This example nicely illustrates how team members combined the needed knowledge of aerospace and design, this latter knowledge being acquired across multiple industries.

Job hoppers such as Steen Strand build their unique knowledge by having exclusively worked in another industry than the target industry or by having hopped across multiple industries. Either type of experience expands the scope of knowledge of the founding team and is likely to be what the teams with shared experience in the target industry are looking for. Thus, I posit that:

Hypothesis 3: The effect of shared experience of the team in the target industry is positively moderated by the inclusion of job hoppers on the founding team who primarily worked outside the target industry.

Complementary effect of job hoppers in teams with prior shared experience outside the target industry

Founding teams with prior shared experience outside the target industry have at hand common organizational knowledge and routines that are different from the ones used in the industry they enter. This organizational knowledge and the related routines therefore need to be adapted to the industry the teams enter. As the organizational knowledge and routines tend to be rigid or inert, the adaptation is a costly process (Rawley, 2010). Job hoppers with experience in the target industry can decrease the adaptation cost by disrupting the existing routines and adapting them to the target industry.

These teams have at hand knowledge that is, by definition, different from the mainstream knowledge in the industry. Therefore their innovation is more likely to rest on incorporating the industry knowledge. The purpose of the job hoppers is to deepen the knowledge of the startup team of the industry it enters rather than to expand the scope of knowledge, which is probably already broad due to the outside industry experience.

The literature on diversifying entrants shows that firms have incentives to enter other industries to expand the use of their capabilities and acquire new markets. For instance, Holbrook and colleagues showed that Motorola entered the semi-conductor industry with electrochemical knowledge they could apply in this industry (Holbrook et al, 2000; Chen, Williams, & Agarwal, 2012). In the car industry, many entrants came from related industries such as carriage and bike manufacturers (Carroll, Bigelow, Seidel, & Tsai, 1996). Transposing these observations to the new venture context, one can expect founding teams to be tempted to apply their knowledge to another industry. Tesla Motors, an electric sports car company, is an illustration of such a case. In the 2000s, an electrical engineer, Martin Eberhard, and a computer scientist, Marc Tarpenning, started working on the idea of an electric sports car. They both worked in the computer and software industries and even developed an e-book together for NuvoMedia. Soon after the takeover of NuvoMedia, they founded Tesla Motors and included in their team, among others, JB Straubel, an energy engineer who had experience in designing engines. Later on, top managers from car manufacturing companies were added to the team. This case illustrates the creation of a car-manufacturing venture by individuals passionate about the concept and who were able to form their team with individuals like Straubel who complemented their knowledge and could set the technology into motion.

Although any type of job hopper can question the routines of a team with prior shared experiences, teams with prior shared experience outside the target industry need job hoppers to bring knowledge relevant to the target industry to have a constructive effect on the team's organization. If they do not bring that knowledge, it might be difficult to recreate routines that would work in the industry context. Second, it would also be difficult for the startup to enter in the industry with little or no knowledge of the industry. An extensive body of work has demonstrated that, for technological reasons or market intelligence, a tie to the industry was a key driver of success (Agarwal et al., 2004; Chatterji, 2009; Delmar & Shane, 2006). Third, if the job hoppers bring knowledge that is related neither to the target industry nor to the rest of the team's knowledge, the team is overloaded and cannot manage so much knowledge coming from various sources (Koput, 1997). Thus, in the case of teams with prior shared experience outside the target industry, I expect that job-hoppers who worked primarily in the target industry are beneficial and posit that:

Hypothesis 4: The effect of the shared experience of the team outside the target industry is positively moderated by the inclusion of job hoppers on the founding team who primarily worked inside the target industry.

DATA AND METHODS

I use an extract of the confidential Longitudinal Employer Household Dynamics dataset (LEHD), which links employees to employers in the US over almost twenty years. The LEHD is constructed from unemployment insurance records and provides quarterly information on all the employees for which the employers pay into the state unemployment insurance fund (McKinney & Vilhuber, 2011). As all employers are required by law to pay unemployment insurance, the LEHD coverage is universal with the exception of self-employed workers and government workers. From this universe of firms, I select all the startups created between 2000 and 2006 in five technological industries[3] in 18 US states. The five industries at the three-digit NAICS level are the following: Fabricated Metal Product Manufacturing; Machinery Manufacturing; Computer and Electronic Product Manufacturing; Electrical Equipment, Appliance, and Component Manufacturing; and Transportation Equipment Manufacturing. I choose these industries because they rely on knowledge to create new products and services, and they offer a favorable environment for startup creation (Carroll et al., 1996; Holbrook et al., 2000; Klepper, 2002; Klepper, 2007). Also, these industries exhibit relatively stable employment relationships. This is important when working with the LEHD because the

[3] The four-digit NAICS level industries that are used in the methodology and analysis are described in Table A.1 of the appendix.

data include all types of workers, including workers for which it could be difficult to identify a main job or a commitment to the labor market. The creation of a startup appears in the data as the introduction of a new establishment identification number. Because this establishment could belong to an existing firm, I check that the new establishment identification number can be linked to a new firm identification number in the bridge of the Longitudinal Business Dynamics (LBD). Because existing firms can change tax identification numbers or create spinoffs with a different tax identification number than theirs, I also discard new establishments that have strictly more than 30 employees at the end of their first year or at their last quarter if they did not survive for a full year. For this last step, I identify all the startups' employees. Among these, I drop all the employees who earned less than $10,000 a year on average over their career because they are probably not committed to the labor market (Campbell, Ganco, Franco, & Agarwal, 2012). I then restrict my sample to startups with at least two employees to be able to study the team aspect. These early employees compose the founding team. While these early employees might not all be startup owners[4], their decisions and actions have long-lasting consequences for the startup such that they are considered part of the founding team (Stinchombe, 1965; Boeker, 1988; Eisenhardt & Schoonhoven, 1990; Baron et al., 1999; Beckman & Burton, 2008). The final sample is made up of 6,000 startups and 31,000 startup year observations[5].

[4] The ownership information is not available in the LEHD.
[5] The sample size is rounded for confidentiality reasons.

Variables

The characteristics of the founding team and startup are measured one year after the startup birth. If the startup did not survive for one full year, these variables are computed based on the information available the last quarter of existence. I choose the one-year landmark because the founding employees of the startup are more likely to have joined by that time rather than at the birth of the startup where some of them might still have another full-time job. To compute the teams' various experiences, I retrace the career of each team member. Since the LEHD time coverage starts in 1991 for most states[6], I am able to observe at least 10 years of prior experience for the eldest employees of the sample. I take into account only the team members' main jobs, the jobs for which they received their highest earnings in a given year, to compute the experience variables (Hyatt & McEntarfer, 2012; Campbell et al., 2013).

The dependent variable is the **startup survival**, which is a relevant measure of performance for young firms (Agarwal et al., 2004; Geroski, 1995; Geroski, Mata, & Portugal, 2010; Phillips, 2002). The variable is coded 1 in any year the startup is alive and 0 for the year the startup fails. I observe survival from 2000 up to the last quarter of 2008 when my LEHD extract stops. It means that I can observe between a maximum of nine and three years of survival for firms created between 2000 and 2006, respectively. On average, around 27% of all the startups failed during the period I examined. I also checked whether the startups were acquired, in which case, the last year observed as an independent firm is coded 1 and the following years are not included.

[6] For detailed time coverage by state, please refer to Table A.2 in the appendix.

I use six time-invariant explanatory variables and their interactions. **Prior shared experience** relates to the knowledge and routines the team has inherited from their work in the incumbent firm for which the team worked before founding the startup. Accordingly, I measure this variable as the number of years of experience the team worked together in the incumbent. More specifically, because the LEHD uses establishment as its key unit of analysis, I am able to focus on teammates who worked in the same establishment at the same time. This strengthens the fact that they share similar knowledge and had the opportunity to collect information on each other directly or by hearsay. As encountered by other studies on teams (e.g. Kor, 2003), these teams are almost never made entirely of team members coming from the same previous employer; therefore, I identify the largest set of team members who came from the same incumbent and use this set of team members to compute the variable. I determine the largest set by counting the number of team members who worked together the year before joining the startup. For instance, if there were four team members in the team and if two of them came from the same employer the year before starting the new venture, they would form the main set. In case of a tie, I used the set with the highest earnings the year before the startup creation. If none of the team members worked in the same firm before joining the new venture, the prior shared experience is null. Thirty-seven percent of the founding teams have shared experience. When they do, the average length is 2.4 years.

Prior shared experience in the target industry relates to the knowledge and routines the team has inherited from their work in the same industry incumbent. Once I identified the set, I used the number of years the set has spent working together in the same firm that is part of the target industry at a 4-digit level prior to creating their startup[7]. If one of the team members worked longer in that same firm by herself, this additional experience is not captured in this variable but is in the team's average experience variable.

Prior shared experience outside the target industry is the number of years the largest set of team members has spent working together in the same firm, which is not part of the target industry. Both prior shared experience variables, within and outside the target industry, are mutually exclusive.

The inclusion of job hoppers in the founding team is measured by **the number of job hoppers** employed by the startup after one year of existence. Job hoppers are individuals who in the five years before joining the startups worked in at least two firms. I only include workers who entered the data at least five years before being employed by the startup. I use this fixed time period to avoid comparisons between workers who had the chance to hop and workers who are at risk of hopping. I also add performance constraints to ensure that job hoppers changed jobs by choice and not because they were laid off for poor performance. The constraints are the following: their earnings did not decrease when they changed jobs; and their average yearly earnings over the 5 years were on average $20,000 or more. I use the average salary to avoid including workers who did not work for a consequent part of their time before creating the startup. Twenty-one percent of the founding teams include one or more job hoppers. When they do, the average number is 1.6 hoppers. Given the studied industries, these job hoppers include,

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[7] Other researchers have averaged the time each pair of team members worked together in the past to measure shared experience (Reagans et al., 2005; Zheng, 2012). This method is not appropriate in my case because the measure would not capture the common knowledge and routines that the team inherited from the same incumbent firm but rather capture knowledge acquired across various past experiences in pairs.

among others, assemblers, cutters, welders, machinists, supervisors, engineers, researchers, and managers. The results are robust with various measures of job hoppers: using a dummy instead of a continuous number of job hoppers; using an average yearly earnings of $30,000 instead of $20,000; and using three job changes over all their prior years I can observe (i.e. up to fifteen years) instead of two job changes over five years.

Number of job hoppers who primarily worked outside the target industry (outside job hoppers) is made up of the job hoppers who worked for firms that do not belong to the target industry, and the job hoppers who worked for more firms that do not belong to the target industry than firms that do. In the case of a tie, the industry of the last employer is picked.

Number of job hoppers who primarily worked inside the target industry (inside job hoppers) is the sum of job hoppers who worked exclusively for firms that belong to the target industry, and the job hoppers who worked for more firms that belong to the target industry than firms that do not belong to the target industry. In the case of a tie, the industry of the last employer is picked. The two job hopper categories are mutually exclusive.

Control variables. As the explanatory variables relate to a specific type of experience and to the number of a specific type of team members, it is important to control for the remaining types of experience and the total number of team members. I included four controls regarding these matters. The team's total experience is the average number of years all team members worked before founding the startup. The left-censored experience dummy takes the value one when at least one of the team members worked the first year the LEHD coverage starts and zero, otherwise. The team entrepreneurial experience is the team average number of startups the teammates created before joining the focal startup. The team size is the number of founding team members who are the number of employees of the startups at its 5^{th} quarter or at its last quarter if the startup fails before its 5^{th} one. Note that team size is also a proxy for the size of the entrepreneurial opportunity.

I also need to control for the ability of the teammates and the quality of the entrepreneurial opportunity to take care of the endogeneity issue. It is likely that teams with higher ability and/or a better opportunity will be able to attract better job hoppers and thus survive longer (Agarwal et al., 2013). To control for the teammates' ability, I use the average earnings of the team the year before the new startup's birth (team's average earnings$_{t-1}$) transformed with a natural logarithm (Agarwal et al., 2013; Braguinsky et al., 2012). To control for the quality of the entrepreneurial opportunity the team pursues, I use the natural logarithm of the payroll of the new venture at the end of the first year, which is consistent with prior work (Agarwal et al., 2013).

I also control for the demographic characteristics of the founding team members by including the team members' average age, the share of males on the team and the share of college educated teammates. The only time variant variables that relate to the startup are the startup age and age squared, they control for the liability of newness of the new venture. I also add the natural logarithm of the yearly number of new establishments in the county of the new venture each year to control for the economic conditions surrounding the startups. The other controls are: year dummies; industry dummies; and region dummies[8]. Table 3.1 presents the descriptive statistics and correlation matrix.

Model

My goal is to test survival with a discrete hazard model where the period of survival is divided into discrete units of one year each (Bayus & Agarwal, 2007; Agarwal et al., 2013). To do so, I set up the dataset as a panel where all the variables are reported for each year of survival and for one year of failure, if any. I tested the likelihood of survival an additional year using a linear probability model (LPM). The choice of a linear model was driven by the importance of the interaction terms to test the hypotheses and by the disclosure procedure of the US Census Bureau, which makes it difficult to disclose split samples to correctly analyze interactions with a discrete choice model (Hoetker, 2007). To account for the heteroscedasticity with LPM, I included robust standard errors clustered by firm (Cameron and Trivedi, 2009). I also checked that the number of out-of-bound predictions of the linear model was limited (i.e. less than 4%), making the use of the model acceptable. I also ran cloglog and logit models with the main effects and the control variables and found consistent results to the LPM: prior shared experience; prior shared experience in the target industry; and prior shared experience outside the target industry being positive and significant. Finally, as suggested by Horrace and Oaxaca (2006), I reran the LPM regressions while excluding the predictions that were out-of-bounds and found the same results.

[8] I used dummy regions instead of state dummies because some states had too few startups. The regions are the following: the West, the South, the Midwest and the Northeast following http://www.census.gov/geo/maps-data/maps/pdfs/reference/us_regdiv.pdf. The correspondence between states and regions is shown in Table A2.

Table 3.1 Descriptive statistics and correlation matrix (n= 6,000 startups)

	Variables	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11
1	Survival	0.95	0.22	1.00										
2	Prior shared experience (PSE)	0.89	1.76	0.02	1.00									
3	Prior shared experience in the target ind.	0.35	1.19	0.02	0.60	1.00								
4	Prior shared experience outside the target ind.	0.54	1.41	0.00	0.74	-0.10	1.00							
5	Job hoppers	0.33	0.87	-0.02	0.05	0.01	0.05	1.00						
6	Inside job hoppers	0.06	0.42	0.00	0.04	0.10	-0.04	0.55	1.00					
7	Outside job hoppers	0.26	0.73	-0.02	0.04	-0.04	0.08	0.88	0.07	1.00				
8	Team's average experience	6.63	2.89	0.02	0.23	0.15	0.16	0.16	0.09	0.14	1.00			
9	Team average # of entrepreneurial exp.	0.40	0.40	0.00	0.04	0.03	0.03	0.02	0.00	0.02	0.25	1.00		
10	Team members' average age	39.33	7.63	-0.01	0.18	0.14	0.10	0.10	0.07	0.08	0.29	0.08	1.00	
11	Share of males	0.79	0.24	-0.01	0.04	0.02	0.04	0.01	0.00	0.02	0.08	0.07	-0.03	1.00
12	Share of college-educated team members	0.20	0.22	0.01	0.11	0.07	0.08	0.10	0.05	0.09	0.07	0.02	0.22	-0.04
13	Team size	6.25	5.77	0.00	0.13	0.11	0.07	0.41	0.22	0.36	0.05	-0.04	0.06	-0.02
14	Team's average earnings $_{t-1}$ (log)	9.51	2.07	-0.01	0.19	0.10	0.15	0.18	0.08	0.17	0.37	0.10	0.08	0.07
15	Startup age	3.67	2.50	-0.05	-0.01	-0.01	0.00	-0.02	-0.01	-0.02	-0.12	-0.02	-0.04	-0.01
16	Startup age squared	19.68	40.91	-0.01	-0.01	-0.02	0.00	0.00	-0.01	0.00	-0.08	-0.02	-0.02	-0.01
17	Startup payroll $_{t}$ (log)	10.98	1.33	0.02	0.02	0.02	0.00	0.25	0.12	0.23	0.07	-0.12	0.02	-0.03
18	Left-censored experience	0.26	0.44	0.01	0.12	0.10	0.06	0.12	0.08	0.10	0.37	0.08	0.10	0.05
19	Number of new establishments (log)	8.69	1.84	-0.01	-0.02	-0.04	0.01	0.08	0.03	0.08	0.05	-0.05	0.04	-0.11

		12	13	14	15	16	17	18	19
12	Share of college-educated team members	1.00							
13	Team size	0.01	1.00						
14	Team's average earnings $_{t-1}$ (log)	0.06	0.19	1.00					
15	Startup age	0.01	-0.02	0.00	1.00				
16	Startup age squared	-0.01	-0.02	0.00	0.82	1.00			
17	Startup payroll $_{t}$ (log)	0.03	0.48	0.22	-0.04	-0.03	1.00		
18	Left-censored experience	0.00	0.24	0.17	-0.02	-0.03	0.15	1.00	
19	Number of new establishments (log)	0.09	-0.04	-0.02	0.11	0.10	0.08	-0.11	1.00

RESULTS

Table 3.1 presents the descriptive statistics and the correlations. Table 3.2 presents the main regressions and results. In Model 1, I report the main effects of the independent variables and find that shared experience is positive and significant at 1% level, which is consistent with H1. The control variables are highly consistent in sign and significance across models. Team average experience is positive and significant at 1%. Team average earnings in t-1 have a negative and significant effect at 1%, which might reflect the opportunity costs of teammates who had high earnings before becoming entrepreneurs. The payroll of the new venture at the end of the first year, which proxies for the quality of the business opportunity, is positively related to survival and significant at 1%. Two demographic characteristics, average age and share of males, turn out negative and significant at 1% while the share of college-educated teammates is positive and significant at 5%. I also find an inverted-U shape relationship between the new venture age and the survival, which should be interpreted with caution because the inflection point is at eleven years – out of the scope of the data. I do not find a statistically significant relationship between survival and team size, the left-censored experience dummy, or the number of new establishments in the county and the year of the startup creation. The insignificant effect of the left-censored experience dummy probably suggests that the main effect of experience is captured by the team average experience. The insignificant effect of team size is probably due to the fact that the size of the startup is also captured by the payroll. The number of new establishments in the county of the startup was supposed to proxy for the competition for capital and, if applicable, for customers in the location of the startup. The region and industry dummies might capture this competition effect.

In Model 2, I add the interactions between the prior shared experience and the total number of job hoppers. The prior shared experience of the founding team has a positive and significant effect on survival (H1). However, the significance level is 10% instead of 1% in Model 1. An additional year of shared experience reduces the failing rate by 2.4%. The main effect of the number of job hoppers is negative and significant at 1%. When job hoppers are included in any kind of teams, their effect is detrimental for the survival of the teams. Teams that do not have an established knowledge base are probably not able to take advantage of the job hoppers' knowledge diversity. By contrast, they probably suffer from their disruption. To test hypothesis 2, I enter the interaction between the total number of job hoppers and the shared experience, which is significant at the 5% level. The marginal effect of the inclusion of one job hopper is only positive when the team has more than three years of shared experience. With three years of shared experience, the inclusion of one job hopper decreases the likelihood of failing the following year by 6.2%.

In Model 3, I split the shared experience into two categories: shared experience in the target industry and shared experience outside the target industry. I also add the two categories of job hoppers: outside job hoppers and inside job hoppers. The shared experience in the target industry is positive and significant at the 1% level, while the shared experience outside the target industry is positive but insignificant. The number of outside job hoppers is negative and significant at the 1% level while the number of inside job hoppers is insignificant. This suggests that outside job hoppers are not beneficial for any type of teams. Job hoppers might create too much disruption and bring knowledge that cannot be utilized by the team and, thus, be detrimental.

In Model 4, I test the interactions between the prior shared experiences and different kinds of job hoppers. The interaction between the prior shared experience in the target industry and outside job hoppers is positive and significant at 1%, consistent with H3. For teams with shared experience within the target industry, the inclusion of one outside job hopper is beneficial when the team has more than two year of shared experience. More specifically, for a team with exactly two years of prior shared experience in the target industry and one outside job hopper, the failure rate decreases by 12.4%. Within the range of the variables, the multiplier effect is large. For instance, for teams with shared experience of three years within the target industry, the additional effect of one job hopper with outside experience decreases the failure rate by around 26.8%. Examining teams with prior shared experience outside the target industry, I find that the interaction between their experience and the inside job hoppers is positive and significant at 5%, supporting H4. The inclusion of one job hopper is already beneficial when the team has a bit more than one year of prior shared experience outside the target industry. For a team with two years of shared experience outside the target industry and one inside job hopper, the failure rate decreases by 13.2%.

Table 3.2 Main regressions

	Main effects 1		Interactions 1		Main effects 2		Interactions 2	
	(1)		(2)		(3)		(4)	
Prior shared experience (PSE)	0.0017***	(0.0007)	0.0012*	(0.0007)				
PSE x job hoppers			0.0026**	(0.0012)				
Job hoppers	-0.0052***	(0.0018)	-0.0083***	(0.0024)				
PSE in the target ind.					0.0029***	(0.0008)	0.0022**	(0.0009)
PSE in the target ind. x inside job hoppers							0.0020	(0.0035)
PSE in the target ind. x outside job hoppers							0.0050***	(0.0018)
PSE outside the target ind.					0.0010	(0.0009)	0.0005	(0.0009)
PSE outside the target ind. x inside job hoppers							0.0066**	(0.0028)
PSE outside the target ind. x outside job hoppers							0.0018	(0.0016)
Inside job hoppers					-0.0041	(0.0036)	-0.0076	(0.0058)
Outside job hoppers					-0.0056***	(0.0021)	-0.0082***	(0.0027)
Team's average experience	0.0022***	(0.0006)	0.0022***	(0.0006)	0.0021***	(0.0006)	0.0021***	(0.0006)
Left-censored experience	-0.0042	(0.0034)	-0.0040	(0.0034)	-0.0042	(0.0034)	-0.0040	(0.0034)
Team average # of entrepreneurial exp.	-0.0031	(0.0033)	-0.0031	(0.0033)	-0.0031	(0.0033)	-0.0031	(0.0033)
Team size	-0.0002	(0.0003)	-0.0002	(0.0003)	-0.0002	(0.0003)	-0.0002	(0.0003)
Team members' average age	-0.0006***	(0.0002)	-0.0006***	(0.0002)	-0.0006***	(0.0002)	-0.0006***	(0.0002)
Share of males	-0.0170***	(0.0055)	-0.0170***	(0.0055)	-0.0168***	(0.0055)	-0.0167***	(0.0055)
Share of college educated team members	0.0146**	(0.0061)	0.0148**	(0.0061)	0.0147**	(0.0061)	0.0148**	(0.0061)
Team's average earnings $_{t-1}$ (log)	-0.0024***	(0.0007)	-0.0024***	(0.0007)	-0.0024***	(0.0007)	-0.0023***	(0.0007)
Startup payroll $_t$ (log)	0.0067***	(0.0012)	0.0067***	(0.0012)	0.0067***	(0.0012)	0.0067***	(0.0012)
Startup age	-0.0110***	(0.0021)	-0.0110***	(0.0021)	-0.0110***	(0.0021)	-0.0110***	(0.0021)
Startup age squared	0.0005***	(0.0002)	0.0005***	(0.0002)	0.0005***	(0.0002)	0.0005***	(0.0002)
Number of new establishments (log)	-0.0010	(0.0008)	-0.0009	(0.0008)	-0.0010	(0.0008)	-0.0009	(0.0008)
Constant	0.9838***	(0.0207)	0.9831***	(0.0207)	0.9843***	(0.0207)	0.9837***	(0.0207)
Number of observations	31000		31000		31000		31000	

Year dummies, industry dummies and region dummies are included. Robust and clustered standard errors. Two-sided tests, * p<.10, ** p<.05, *** p<.01.

Robustness checks

There are a few alternative explanations for the effect of job hoppers to discuss. First, job hoppers might be beneficial because they come from another organization and can notice what is missing or not working in the inherited knowledge of the rest of the team. In this case, the hopping component would not matter but only the fact that their prior employment differs from the rest of the team. To test this alternative explanation, I created a variable called *number of team members with five year of experience,* which has the same earnings and time constraints as the job hoppers (i.e. an average of at least $20,000 a year during the five years prior to the startup) but does not include the hopping in the sense that these team members could work for only one organization other than the parent firm during these five years. I ran the regressions with this new variable in Table 3.3 Models 1 and 2 and the interactions are insignificant. This means that the hopping indeed matters.

Table 3.3 Regressions with team members without parent firm experience or hopping

	Interactions 1		Interactions 2	
	(1)		(2)	
Prior shared experience	0.0017**	(0.0007)		
PSE x team members	-0.0002	(0.0018)		
Team members	-0.0090**	(0.0037)		
PSE in the target ind.			0.0031***	(0.0009)
PSE in the target ind. x inside team members			-0.0160	(0.0115)
PSE in the target ind. x outside team members			0.0005	(0.0022)
PSE outside the target ind.			0.0008	(0.0009)
PSE outside the target ind. x inside team members			0.0069	(0.0046)
PSE outside the target ind. x outside team members			0.0002	(0.0025)
Inside team members			-0.0117***	(0.0041)
Outside team members			0.0081	(0.0092)
Team's average experience	0.0021***	(0.0006)	0.0021***	(0.0006)
Left-censored experience	-0.0043	(0.0034)	-0.0043	(0.0034)
Team average # of entrepreneurial exp.	-0.0031	(0.0033)	-0.0032	(0.0033)
Team size	-0.0004	(0.0003)	-0.0004	(0.0003)
Team members' average age	-0.0006***	(0.0002)	-0.0006***	(0.0002)
Share of males	-0.0172***	(0.0055)	-0.0173***	(0.0055)
Share of college educated team members	0.0146**	(0.0061)	0.0144**	(0.0061)
Team's average earnings $_{t-1}$ (log)	-0.0024***	(0.0007)	-0.0024***	(0.0007)
Startup payroll $_t$ (log)	0.0069***	(0.0012)	0.0068***	(0.0012)
Startup age	-0.0111***	(0.0021)	-0.0111***	(0.0020)
Startup age squared	0.0005***	(0.0002)	0.0005***	(0.0002)
Number of new establishments (log)	-0.0010	(0.0008)	-0.0010	(0.0008)
Constant	0.9830***	(0.0208)	0.9858***	(0.0208)
Number of observations	31000		31000	

Year dummies, industry dummies and region dummies are included. Robust and clustered standard errors. Two-sided tests, * p<.10, ** p<.05, *** p<.01

Second, job hoppers might positively moderate shared experience because they bring entrepreneurial knowledge to the teams. In other words, job hoppers might be serial entrepreneurs, and their effect on shared experience would be due to this extensive entrepreneurial experience. To test if job hoppers are beneficial for teams regardless of their past entrepreneurial experience, I build job hoppers variables that exclude the job hoppers who worked in an establishment that was one year or younger and had less than 31 employees. Table 3.4 models 1 and 2 show that the hypotheses are still supported with weaker significance level – 5% for the first two interactions and 10% for the last one. This is due to the fact that the number of job hoppers is much smaller after the exclusion of the ones with entrepreneurial experience.

Table 3.4 Regressions with job hoppers without entrepreneurial experience

	Interactions 1		Interactions 2	
	(1)		(2)	
Prior shared experience	0.0013*	(0.0007)		
PSE x job hoppers	0.0029**	(0.0014)		
Job hoppers	-0.0070***	(0.0026)		
PSE in the target ind.			0.0027***	(0.0009)
PSE in the target ind. x inside job hoppers			0.0007	(0.0015)
PSE in the target ind. x outside job hoppers			0.0043**	(0.0020)
PSE outside the target ind.			0.0010	(0.0009)
PSE outside the target ind. x inside job hoppers			0.0040*	(0.0024)
PSE outside the target ind. x outside job hoppers			-0.0003	(0.0014)
Inside job hoppers			-0.0266	(0.0180)
Outside job hoppers			-0.0177**	(0.0080)
Team's average experience	0.0021***	(0.0006)	0.0021***	(0.0006)
Left-censored experience	-0.0039	(0.0034)	-0.0043	(0.0034)
Team average # of entrepreneurial exp.	-0.0034	(0.0033)	-0.0038	(0.0033)
Team size	-0.0003	(0.0003)	-0.0006**	(0.0003)
Team members' average age	-0.0006***	(0.0002)	-0.0006***	(0.0002)
Share of males	-0.0173***	(0.0055)	-0.0173***	(0.0055)
Share of college educated team members	0.0145**	(0.0061)	0.0147**	(0.0061)
Team's average earnings $_{t-1}$ (log)	-0.0024***	(0.0007)	-0.0024***	(0.0007)
Startup payroll $_{t}$ (log)	0.0067***	(0.0012)	0.0066***	(0.0012)
Startup age	-0.0110***	(0.0020)	-0.0109***	(0.0020)
Startup age squared	0.0005***	(0.0002)	0.0005***	(0.0002)
Number of new establishments (log)	-0.0010	(0.0008)	-0.0011	(0.0008)
Constant	0.9855***	(0.0207)	0.9883***	
Number of observations	31000		31000	

Year dummies, industry dummies and region dummies are included. Robust and clustered standard errors. Two-sided tests, * p<.10, ** p<.05, *** p<.01

Job hoppers might have worked in the parent firm where the rest of the team gained their prior shared experience. Thus, one can wonder whether the job hoppers' beneficial effect is due to a mix of experience at the parent firm and other experiences. The theoretical argument does not depend on this parent experience and, therefore, I excluded job hoppers with parent firm experience and re-ran the regressions.

In Table 3.5, Models 1 and 2, the results are presented and the same hypotheses are still supported. For the same reason as discussed before, the significance weakens and is down to 10%.

Table 3.5 Regressions with job hoppers without parent firm experience

	Interactions 1		Interactions 2	
	(1)		(2)	
Prior shared experience	0.0013*	(0.0007)		
PSE x job hoppers	0.0024*	(0.0013)		
Job hoppers	-0.0104***	(0.0032)		
PSE in the target ind.			0.0026***	(0.0009)
PSE in the target ind. x inside job hoppers			-0.0015	(0.0032)
PSE in the target ind. x outside job hoppers			0.0029*	(0.0017)
PSE outside the target ind.			0.0010	(0.0009)
PSE outside the target ind. x inside job hoppers			0.0040*	(0.0024)
PSE outside the target ind. x outside job hoppers			-0.0013	(0.0017)
Inside job hoppers			-0.0094	(0.0296)
Outside job hoppers			-0.0270***	(0.0089)
Team's average experience	0.0021***	(0.0006)	0.0021***	(0.0006)
Left-censored experience	-0.0039	(0.0034)	-0.0044	(0.0034)
Team average # of entrepreneurial exp.	-0.0031	(0.0033)	-0.0034	(0.0033)
Team size	-0.0003	(0.0003)	-0.0005**	(0.0003)
Team members' average age	-0.0006***	(0.0002)	-0.0006***	(0.0002)
Share of males	-0.0171***	(0.0055)	-0.0173***	(0.0055)
Share of college educated team members	0.0147**	(0.0061)	0.0147**	(0.0061)
Team's average earnings $_{t-1}$ (log)	-0.0024***	(0.0007)	-0.0024***	(0.0007)
Startup payroll $_t$ (log)	0.0068***	(0.0012)	0.0067***	(0.0012)
Startup age	-0.0110***	(0.0021)	-0.0110***	(0.0020)
Startup age squared	0.0005***	(0.0002)	0.0005***	(0.0002)
Number of new establishments (log)	-0.0010	(0.0008)	-0.0010	(0.0008)
Constant	0.9836***	(0.0207)	0.9873***	(0.0207)
Number of observations	31000		31000	

Year dummies, industry dummies and region dummies are included. Robust and clustered standard errors. Two-sided tests, * p<.10, ** p<.05, *** p<.01

A fourth alternative explanation could be that job hoppers are a proxy for the team's diverse experience. Job hoppers could be a proxy for the average number of past employers for which the whole team worked or a proxy for long experiences in and outside the target industry. In these two cases, the job hoppers' synthesis of various experiences and their dual role of routines disruption and innovation would not matter.

To test the first of these two alternatives, I constructed two variables: the team average number of previous employers in the target industry and the team average number of previous employers outside the target industry. In Table 3.6 Model 1, the shared experience outside the target industry is significant and positive as before. The average number of previous employers outside the startup is negative and significant. None of the interactions between both shared experiences and both average numbers of previous employers turn out significant. Further, I use a Wald test to check whether the coefficients in the main model and in this model are significantly different. PSE in target industry x outside job hoppers is significantly different from PSE in the target ind. x # previous firms outside the target ind. at 10% and from PSE in the target ind. x # extra experience outside the target ind. at 1%. This confirms that job hoppers add value to the team that is not just represented by a team's various past employers.

To test the second of the two alternatives, I construct two other additional variables: the extra experience outside and inside the target industry. Extra experience means the experience that is not part of the shared experience. For instance, if the team worked three years together in an incumbent and, beforehand, one team member worked 4 years in the target industry, this extra experience is taken into account as an average for the team (i.e. 4/3= 1.33 years). Table 3.7 Model 1 presents the results with the team's average total experience being dropped. Two main effects are significant: the extra experience outside the target industry is significant and negative and the shared experience in the target industry is still significant and positive. The interaction between these two variables is negative and significant. The extra experience from outside target industry curbed the positive impact of the shared experience within the target industry.

Further, I use a Wald test to check whether the coefficients in the main model and in this model are significantly different. PSE outside target industry x inside job hoppers is significantly different from PSE outside the target ind. x # previous firms in the target ind. at 5% and from PSE outside the target ind. x # extra experience in the target ind. at 1%. These results show that knowledge from other industries brought by the team is detrimental and support the idea that outside knowledge is more easily integrated by one or a few individuals than by a whole team.

Table 3.6 Interactions with team's number of previous firms (employers)

	Interactions 2	
	(1)	
PSE in the target ind.	0.0042*	(0.0024)
PSE outside the target ind.	0.0002	(0.0020)
PSE in the target ind. x # previous firms in the target ind.	-0.0030	(0.0023)
PSE in the target ind. x # previous firms outside the target ind.	0.0002	(0.0008)
PSE outside the target ind. x # previous firms in the target ind.	-0.0031	(0.0044)
PSE outside the target ind. x # previous firms outside the target ind.	0.0002	(0.0009)
Average number of previous firms in the target industry	-0.0031	(0.0040)
Average number of previous firms outside the target industry	-0.0056***	(0.0015)
Team's average experience	0.0035***	(0.0007)
Left-censored experience	-0.0047	(0.0034)
Team average # of entrepreneurial exp.	-0.0005	(0.0034)
Team size	-0.0006**	(0.0003)
Team members' average age	-0.0008***	(0.0002)
Share of males	-0.0176***	(0.0055)
Share of college educated team members	0.0105*	(0.0061)
Team's average earnings $_{t-1}$ (log)	-0.0024***	(0.0007)
Startup payroll $_{t}$ (log)	0.0069***	(0.0012)
Startup age	-0.0112***	(0.0020)
Startup age squared	0.0005***	(0.0002)
Number of new establishments (log)	-0.0011	(0.0008)
Constant	0.9965***	(0.0207)
Number of observations	31000	

Year dummies, industry dummies and region dummies are included. Robust and clustered standard errors. Two-sided tests, * p<.10, ** p<.05, *** p<.01

Table 3.7 Interactions with team's extra experiences

	Interactions 2	
	(1)	
PSE in the target ind.	0.0038***	(0.0013)
PSE outside the target ind.	0.0004	(0.0012)
PSE in the target ind. x extra exp. in the target ind.	-0.0002	(0.0005)
PSE in the target ind. x extra exp. outside the target ind.	-0.0009***	(0.0004)
PSE outside the target ind. x extra exp. in the target ind.	-0.0021	(0.0014)
PSE outside the target ind. x extra exp. outside the target ind.	-0.0003	(0.0003)
Extra exp. in the target ind.	-0.0001	(0.0010)
Extra exp. outside the target ind.	-0.0036***	(0.0005)
Left-censored experience	0.0075**	(0.0033)
Team average # of entrepreneurial exp.	0.0019	(0.0033)
Team size	-0.0008***	(0.0003)
Team members' average age	-0.0004**	(0.0002)
Share of males	-0.0180***	(0.0055)
Share of college educated team members	0.0127**	(0.0061)
Team's average earnings $_{t-1}$ (log)	-0.0000	(0.0007)
Startup payroll $_{t}$ (log)	0.0068***	(0.0012)
Startup age	-0.0131***	(0.0021)
Startup age squared	0.0006***	(0.0002)
Number of new establishments (log)	-0.0004	(0.0008)
Constant	0.9947***	(0.0206)
Number of observations	31000	

Year dummies, industry dummies and region dummies are included. Robust and clustered standard errors. Two-sided tests, * p<.10, ** p<.05, *** p<.01

DISCUSSION

Founders' prior experience is often considered as a major driver of startup performance. However, little is known on the complementarities between experience acquired in same prior setting or different setting such as firms and industries. In this paper, I investigated how the inclusion of job hoppers in founding teams can disrupt shared knowledge and bring complementary knowledge components. By doing so, I highlight a novel mechanism that underlies the knowledge complementarities in founding teams.

Drawing on a rich employee-employer linked dataset, I first establish a baseline relationship: prior shared experience has a positive effect on startup survival (H1). I then analyze the interaction between this prior shared experience and the number of job hoppers in the team. This interaction turns out positive and significant, meaning that job hoppers make the positive effect of shared experience bigger when the prior shared experience is longer than three years (H2). The job hoppers are particular team members that have integrated experiences and knowledge coming from multiple firms. I find that job hoppers who primarily worked outside the target industry complement their team's prior shared experience within the target industry, in the sense that their effect makes the effect of prior shared experience larger when the prior shared experience in the target industry is longer than two years (H3). The interaction between the shared experience outside the target industry and the number of job hoppers who primarily worked inside the target industry is significant and positive as long as the prior shared experience outside the startup is of one year (H4). Teams without experience of the industry they enter clearly benefit from job hoppers with that experience. Importantly, the results show that the main effect of the shared experience outside the target industry is not significant. The prior shared experience outside the target industry should bring to the team a better organization. However, this positive contribution is not strong enough to compensate for other issues such as the lack of target industry knowledge so that the effect would turn out significant. It also important to note that job hoppers main effects are negative suggesting that job hoppers are only beneficial when the startups share knowledge that can be complemented. When a startup does not share any knowledge, job hoppers are probably too disruptive and the extra knowledge they bring can difficulty be incorporated.

In addition to testing the key constructs, I rule out alternative explanations. First, the job hoppers might be beneficial because they come from an organization other than the rest of the team and not because they acquired experiences across multiple organizations. I ruled out that explanation by showing the absence of results with teammates with five years of experience coming from another organization than the rest of the team. Thus the hopping component indeed matters to obtain a positive interaction between shared experience and individuals with unique experience. The second alternative explanation is based on a serial entrepreneurship argument. All the job hoppers could be serial entrepreneurs; thus, rather than bringing knowledge from other industries, they would primarily bring entrepreneurial skills and resources to the team. I ruled out this explanation when, in my robustness checks, I included only the job hoppers who did not work in more than one new venture and showed that the results still hold. Third, job hoppers' positive effect might actually come from their experience in the parent firm of the rest of the team. I thus excluded job hoppers who worked in the parent firm and found similar results. Fourth, the job hoppers might be a proxy for the whole team's average number of past employers. I ruled out this explanation by showing that the interaction with the average number of previous employers is not significant. Fifth, the job hoppers might be a proxy for the effect of a long work experience. I ruled out this explanation by showing that interactions between the shared experiences and the extra experiences within and outside the target industry, respectively, do not have a positive effect either.

Overall, the combination of main results and robustness tests suggests that the two roles of job hoppers, disruption and innovation, are decisive in their positive interaction with the shared experience of the team. If disruption alone was needed, the non-hypothesized interactions should turn out positive as well (i.e. shared experience within target industry and inside job hoppers and shared experience outside the target industry and outside job hoppers). On the other hand, if knowledge from other sources alone were needed, the average extra experiences and average number of previous employers from the robustness checks would have turned out significant as well. By showing that only job hoppers, individuals who bring disruption and other sources of knowledge, positively moderate the prior shared experience of the team, I implicitly support the two underlying theoretical mechanisms.

Limitations

Despite the results and robustness checks, there are several limitations to this study. First, there might be unobserved factors influencing the selection of the team members and affecting the estimation of their effect on the startup performance. One of these factors could be the opportunity that the team pursues. It is difficult to know whether the opportunity is identified first and then the best possible team is created to pursue it or whether the team formed based on personal preferences and then the opportunity is identified and pursued. The former would create a selection bias. I am able to partly address the concern by controlling the ability of the team members and the size of the opportunity they pursue. Because in the study of teams, multiple team characteristics are typically investigated, the use of an instrumental variable for each of these characteristics is difficult. Future research might use newer empirical techniques, such as a multi-sided many-to-many matching model, to control for the mutual selection among all the team members that occurred during the team formation.

There are three limitations pertaining to the use of the LEHD in addressing my research question. First, The LEHD does not identify firm owners, nor provide any kind information on them. Thus, I had to make the assumption that all the employees of the startup the first year are part of the founding team regardless of their actual ownership. Second, to enter the LEHD, a startup has to have employees for which it pays unemployment insurance. Some startups might have developed their business ideas and even product before incorporating and hiring their first employees. Given the data, there is no observation of any pre-employment activities. While it would be interesting to observe the very inception of startups, the LEHD still offers a very detailed coverage of the startup existence. In terms of the empirical estimation, one has to make the assumption that on average, the effects of startups that hire late versus the ones that hire early cancel each other out. Third, this study does not cover the complementarities in the team based on the team members' occupation, such as financial director. Future research could combine the knowledge based on industry experience and the occupation of the team members. This study is limited in doing so because the LEHD does not provide the information about the role of each team member and because, for confidential reasons, it would be difficult to systematically link this information to the current dataset.

CONTRIBUTIONS AND CONCLUSION

Common experience is important for firms, teams and individuals to create and run economic activity. Simultaneously, knowledge from other experiences is needed to innovate. This paper uncovers one of the strategies used by founding teams to reconcile both positions: creating complementarities between a team's shared experience and job hoppers' diverse experience. Delving into the origin of the experience, there is also a tension between deep industry experience and the need for experience acquired in other industries to innovate. Complementarities can be created between shared experience of the target industry and job hoppers' experience of other industries on one hand and between shared experience of another industry and job hoppers' experience in the target industry on the other hand. The main contribution of this paper is, thus, to uncover mechanisms behind the positive impact of experience diversity. Specifically, the paper highlights a complementary effect between shared experience (i.e. majority of the team) and high experience diversity (i.e. job hoppers). By doing so, this paper shows that the effect of experience diversity is multi-dimensional.

Newer research on founding teams has started comparing teammates' experience by investigating the tension between the founders or CEO's experience versus the experience of the rest of the team and by showing that this tension affects strategic choices (Fern et al., 2011; Furr, Cavaretta, & Garg, 2012). This paper expands this research by relaxing the constraints based on the occupation (i.e. CEO) and shows that other types of teammates (i.e. job hoppers) can provide the complementary knowledge.

In the context of the spinout literature, which focuses on entrepreneurs coming from incumbent firms, relevant knowledge acquired during prior experience in these incumbents has always been central (Helfat and Lieberman, 2002). Building on prior research, this paper goes further by examining the complementarities between within industry knowledge and outside industry knowledge. It also highlights the knowledge shared by the team versus the knowledge brought by job hoppers. Second, whereas the spinout literature often compares the spinout performance to other kinds of startups, this paper highlights the drivers of spinout performance heterogeneity, i.e. the inclusion of job hoppers in teams with prior shared experience acquired at an incumbent firm. This opens the doors to more research on the complementarities between shared experience and a team's other characteristics and their effect on spinout performance.

Further, the paper also highlights cases where job hoppers influence positively the firm performance. In strategy, job hoppers are often studied as drivers of knowledge spillover (Saxenian, 1996) or as cases for intellectual property litigations between firms (Agarwal et al., 2009; Ganco et al., 2014). In the human resource field, job hoppers can have bad press because their departures are costly to firms (Mitchell et al., 2001). This paper brings another view on job hoppers by showing that in specific cases they improve the firm performance.

Because entrepreneurial teams are responsible for roughly 85% of all technological ventures created (Wasserman, 2012), this research has significant implications for the entrepreneurial community. The findings suggest that if the entire team or most of its members come from the same incumbent firm, including one or more members with a variety of experiences can significantly increase the chances of survival of the startup. This is therefore an important strategic decision that entrepreneurs have to make. Most entrepreneurs start firms with people they know well (i.e. friends, family or colleagues) and who are similar to them in terms of demographic characteristics (Ruef et al., 2003; Wasserman, 2012). This research encourages future entrepreneurs to pay attention to the past experiences of their acquaintances and study the potential complementary effects that could exist among them. The findings also draw attention to the fact that job hoppers can be detrimental to teams that already exhibit diverse knowledge. For these teams, the integration of job hoppers might be too difficult as they might disrupt knowledge that is not established with most of the team.

In summary, I theorized and found evidence that job hoppers can be beneficial by bringing constructive disruption and innovation to teams with prior shared experiences. This study sheds light on a specific mechanism of experience combination across team members of founding teams.

CHAPTER 4
ESSAY 2
ENTREPRENEURIAL TEAMS' ACQUISITION OF TALENT: A TWO-SIDED APPROACH

INTRODUCTION

Research has long shown that human capital is crucial for startup survival and growth (Cooper & Bruno, 1977; Cooper, Gimeno-Gascon, & Woo, 1994; Eisenhardt & Schoonhoven, 1990). Human capital represents the knowledge and skills that reside in the startups' founding teams and first employees, and is often the only resource on which startups can rely to develop their first entrepreneurial ideas and to attract funding (Shane, 2000; Shane & Stuart, 2002). A common way to build this human capital is to hire talented employees. However, little is known about startups' hiring process. Hiring by startups is rarely observed and is taken for granted as part of other activities that startups execute to survive and grow (Autio, Sapienza, & Almeida, 2000; Delmar & Shane, 2004). The rare exceptions concern the change in the startups' top management team (Beckman & Burton, 2008)

The lack of findings is troublesome because hiring is an important activity that is often difficult to do well. Prior literature often describes the difficulties of firms in assessing the quality of potential hires (Schmidt and Hunter, 1998). These difficulties are even more acute for founders and startups as they have fewer resources and processes dedicated to hiring (Shane, 1996; Wasserman, 2012). Moreover, hiring is not only about a startup selecting the right hire but also about the potential hires deciding to join the startup. Potential hires must also figure out if the job suits them (Halaby, 1988). In the case of startups in their first years of existence, the information that a potential hire can acquire is limited. Also, the risks associated with job loss are higher when working for startups in their early years because they are more likely to fail than established firms (Aldrich & Pfeffer, 1976; Freeman et al., 1983). Overall, although it is crucial for startups to hire talented employees to survive and grow, the phenomenon has not been thoroughly studied.

I fill this research void by examining the mutual selection between the set of startups that hired and the set of employees that got hired in a given market with a novel approach, a two-sided matching model. This model reveals which characteristics influence the mutual selection given the observed matches between startups and employees. I call these employees joiners, individuals who do not create startups but are willing to join them in their early stages (Roach & Sauermann, 2015). The theoretical and empirical framework is constructed to answer three fundamental questions:

1) What startup characteristics affect the joiners' decision to work for a given startup, i.e. what makes a startup an attractive employer relative to other startups?
2) What joiner characteristics affect the startup's decision to hire a given joiner, i.e. what makes a potential joiner an attractive hire on the labor market relative to other potential joiners?
3) What startup and joiner characteristics affect the joiner earnings in the startup once the effect of these characteristics on selection has been accounted for?

To answer these questions, I enter in the model characteristics identified by prior research on human capital in startups such as prior experiences, prior earnings and education. I take an exploratory approach where I remain agnostic regarding the relative weight of each characteristic.

As mentioned, I use a two-sided one-to-many assortative matching model with Bayesian estimation (Sørensen, 2007; Park, 2013; Chen, 2013). This model relies on the assumption that the labor market is a competitive place. Startups compete to hire the best joiners and joiners compete to get hired by the best startups. During the sorting, agents with low attractiveness are pushed down in the ranking while attractive agents are pushed up. Starting with the premise that the observed match is the best match an agent could have obtained given her quality, the model reveals what agent characteristics determine this latent attractiveness. Second, to estimate the joiners' earnings in the startup, I use the ranking in each side as the exogenous variation to avoid the endogeneity problem due to unobserved characteristics that affect the selection and the earnings. More explicitly, the mutual selection between a startup and a joiner depends on their ranking position determined by their own characteristics and on the other startups and joiners' characteristics. However, the earnings of a joiner is exogenous to the other startups and other joiners' characteristics. Thus, the ranking based on the other actors' characteristics is similar to an instrument that relates to an agent's own characteristics without affecting her earnings.

I use the context of startups in technological industries where prior experience is an important resource and, thus, is also likely to be a critical characteristic in the selection model. This context matters because prior research has strongly emphasized the effect of prior experience on startup performance (Agarwal et al., 2004) without capturing its effect on human capital formation (Ruef et al., 2003). I use the employee-employer linked dataset provided by the US Census Bureau (LEHD) to identify startups and their employees including the joiners, and to build the prior experiences of all actors. The startups belong to one of five technological industries and were created between 2000 and 2006 in eighteen US states. The study focuses on the entire population of these startups that hire joiners.

To foreshadow my results, I find that startups with large and college-educated founding teams make more attractive employers. By contrast, startups' founding teams with more white team members, more aliens and team members between forty and fifty years old are less attractive. I also find that joiners with target industry experience of three years or more, of male gender, with a college degree and between thirty and forty years old are more attractive. These results suggest that signals of productivity and growth potential make startups attractive and that target industry experience and signal of productivity as well as ascribed criteria such as gender and age make joiners attractive. Second, joiners' earnings one year after being hired are positively affected by joiners' earnings prior to being hired, the fact of being male and white, and the earnings of the startup founding team before the startup creation.

To summarize, this essay shows that startups that can signal productivity and growth potential are able to attract joiners with specific industry experience. This is an important finding because pre-startup experience in the target industry has been shown to affect startup performance (Agarwal et al., 2004). Thus, even if a startup does not have that pre-experience in its founding team, it can still acquire it later on. No clear signs of homophily based on demographic characteristics were found. This is important because prior work on entrepreneurial team formation found an effect of homophily (Ruef et al., 2003). Homophily might not be a crucial mechanism in the hiring process for technological startups. However, an important demographic finding is that male joiners are strongly preferred over female joiners, which fuels the debate on gender discrimination in the startup context (Khazan, 2015). This essay also shows that prior earnings, gender, and race affect current earnings in a startup. This is an important finding for research on earnings structure (Altonji & Blank, 1999; McCall, 2001), suggesting that disparities exist in startups as well.

On a methodological stance, this essay expands the use of a two-sided matching model to understand selection in the fields of entrepreneurship and strategy (Mindruta, 2013; Mindruta et al., 2014). Too often in the past, discrete choice models were used, although the decision really depended on the agreement and cooperation of two distinct groups. The essay also highlights one solution based on sorting to handle endogenous relationships when instruments are not readily available (Sørensen, 2007; Park, 2013; Chen, 2013).

This research with the two-sided methodology reveals and summarizes practical information for startups, potential joiners and policy makers. As for startups, it informs them about potential strategies to hire and more specifically, which characteristics to develop to appear as an attractive employer to the most promising joiners. As for joiners, this research helps them understand what characteristics make them attractive for startups and what characteristics will affect their earnings. As for policy makers, this research helps them understand what characteristics make a labor force attractive for startups and what discrimination or disparities they might have to fight.

The labor market is a competitive place where startups seek joiners who help them survive and grow and where joiners seek startups in which they can perform well by contributing to the startup development. When a startup hires a joiner, they both enter in a voluntarily formed relationship with the objective to increase their respective performance. To enter in this relationship, startups and joiners select each other based on each other's characteristics that they see as conducive to higher performance. Based on prior research, I identify five characteristics that I enter into the model to explain the phenomenon.

Prior experiences

Experience in the target industry. Founding teams with target industry experience have at hand knowledge that is relevant to the industry their startups enter. This knowledge, which can be technological, market-related, or regulation-related, gives their startups an edge over other startups missing that knowledge (Agarwal et al., 2004; Chatterji, 2009). Thus, joiners are likely to perceive founding teams with target industry experience as potentially more successful in terms of survival, growth and innovation and so, as a more attractive counterpart. Especially, because the joiners take some risk to work for a startup, market knowledge as it relates to identifying underserved customers or better serving customers reinsures the joiners of the viability of the business they join (Agarwal et al., 2004; Delmar and Shane, 2006). Startups are also likely to prefer joiners with target industry experience because workers with such experience tend to perform better (Parent, 2000). They can be up to speed immediately and exploit the knowledge they have acquired with lower adaption costs than workers coming without any target industry experience.

One factor can downplay the effect of target industry experience on the mutual selection. If all the startups at the top of the ranking already have target industry experience, their top choice might be joiners with other types of knowledge to diversify their knowledge base (Sapienza et al., 2004) and to acquire the potential to recombine knowledge and innovate (Katila & Ahuja, 2002; Fleming & Sorenson, 2001). Overall, given the extensive prior findings of positive effect of target industry experience on firm and individual performance, founding teams and joiners with prior experience in the target industry are likely to be attractive partners, i.e. target industry experience positively will affect their ranking in the sorting process.

Entrepreneurial experience. Founding teams' entrepreneurial experience has been shown to have a positive impact on startup performance as well (Delmar & Shane, 2006). Founding teams with prior entrepreneurial experience have acquired organizational knowledge on how to run a new business and on how to manage the first hurdles (Delmar & Shane, 2006). These founding teams are also better at obtaining larger amounts of venture capital funding (Hsu, 2007), and are faster at securing investment and reaching milestones such as IPOs (Shane & Stuart, 2002). These two features are attractive to joiners who took some risks by joining a startup where their employment is more precarious. Thus, founding teams with entrepreneurial experience are likely to be attractive partners, i.e. entrepreneurial experience positively affects their ranking.

Signals of productivity, ability and growth potential

Productivity. Level of education is a well-known signal of productive capabilities for individuals (Spence, 1976; Weiss, 1995). Thus, founding teams with a higher share of educated team members signal productivity. Founding teams with higher levels of education also convey some information on the technological level of the entrepreneurial opportunity. In these technological industries, innovations and more particularly breakthrough innovations rely at least partly on concepts developed in the academic setting (Shah & Panhke, 2014). For instance, significant developments in the semi-conductor industry emerged from research led by university researchers in combination with firms' labs (Holbroock et al. 2000). Highly educated joiners are also attractive partners for startups because they are likely to have more productive capabilities (Spence, 1973) and connections to reservoirs of knowledge from which to draw (Fleming & Sorenson, 2004). Thus, founding teams and joiners with college education are likely to be attractive partners, i.e. education positively affects their ranking.

Ability. While prior target industry experience and prior entrepreneurial experience relate to knowledge about the industry and about how to start a new business, prior earnings encompasses more general ability that affects the individuals' ranks in a firm's hierarchy (Wezel, Cattani, & Pennings, 2006), social connections (Shaw, Duffy, Johnson, & Lockhart, 2005) and access to better information (Agarwal et al., 2013). Further, knowledge without the ability to exploit it should not guarantee higher earnings, which means that prior earnings encompass more information than the acquisition of knowledge. This additional information is summarized under the general term of ability (Braguinsky et al., 2012). High ability individuals who become founders have startups that do better (Agarwal et al., 2013) and do better personally by, for instance, perceiving higher earnings (Braguinsky et al., 2012). This is an important signal for joiners for their upcoming career in the startup. Similarly, startups are likely to prefer joiners with high ability. To sum up, founding teams and joiners with high prior earnings are likely to be attractive partners, i.e. high prior earnings positively affect their ranking.

Growth potential. In addition to signaling the stock of knowledge on which they can rely, founding teams also need to signal their potential to survive and to grow. Large founding teams signal two important features to joiners. First, they signal that the startups pursue a large entrepreneurial opportunity as a large market opportunity, or high-potential opportunity requires more employees in order to start. Second, they signal that the founders were able to find the initial funding to form the team to pursue it (Geroski et al., 2010). Thus, large initial teams signal high potential and the access to resources to, at least, start realizing the potential. Large teams are also more likely to be organized into specialized roles and tasks and to exhibit complementarities of knowledge (Sine, Mitsuhashi, & Kirsch, 2006; Wezel et al., 2006). Thus, a large team conveys a positive signal of possibility of growth and career progression for the joiners and is likely to be an attractive counterpart. Large founding teams are likely to be attractive partners, i.e. founding team size positively affects their ranking.

METHODOLOGY

Model

Motivations

This essay has the objective to answer three questions.

1) What startup characteristics affect the joiners' decision to work for a given startup, i.e. what makes a startup an attractive employer relative to other startups?

2) What joiner characteristics affect the startup's decision to hire a given joiner, i.e. what makes a potential joiner an attractive hire on the labor market relative to other potential joiners?

3) What startup and joiner characteristics affect the joiner performance in the startup once the effect of these characteristics on selection has been accounted for?

To do so, I opt for a one-to-many two-sided matching model. This model was originally developed to determine assignment based on mutual selection between two distinct groups –universities and students during college admission (Gale and Shapley, 1962; Roth and Sotomayor, 1989). In the version that I use, the mutual selection also supplements an outcome equation to answer my third question. Before entering into the model specifications, it is important to understand the two advantages of this model over discrete choice models to answer questions 1 and 2 (Park, 2013). A discrete choice model estimates the choice made by one agent although startups and joiners only enter in an employment relationship if they both agree and select each other simultaneously. Second, a discrete choice model misses the fact that choices are interdependent – if a startup picks a joiner, this joiner is not in the choice set of the next startup. The matching model allows the choices of each entity within a group to interact with the choices of the other entities.

This specific matching model is also used to take care of the endogeneity issue that occurs in outcome or performance regression (Sørensen, 2007). Here is a simple example to understand the issue in this context. I know that experienced founding teams select better joiners but I do not observe all the dimensions that make them better hires. The founding team experience is thus correlated with these unobserved dimensions. The positive effect of a founding team's experience on earnings is thus biased as it includes this extra information on joiners. A classical solution would be to use an instrument for founding team experience that does not correlate with joiner's earnings. However, it is difficult to find good instruments for founding team experience in this simple example, plus potentially for all the other founding team characteristics. Rather than finding these exogenous variables, the matching model uses the sorting as an exogenous variation that affects the selection between the joiners and startups but not the earnings. The sorting plays out as follow. Each agent, founding team or joiner, is ranked against the other agents in their group. The best teams are at the top of the ranking and have the opportunities to choose among all the joiners, whereas the worst teams might be pushed back and have only a few possibilities for joiners. Similarly, the joiners are also ranked and see their choice set of founding teams affected by their characteristics and the characteristics of all the other joiners. The positions in the rankings are relative and depend on each agent's characteristics. For a given match between a team and a joiner, the exogenous variation that is needed to obtain a correct estimation of the earnings is provided by the characteristics of the remaining agents. More precisely, the selection that happens between team i and joiner j is influenced by their own characteristics as well as the characteristics of the remaining agents. Because the characteristics of these remaining agents influence the match between i and j but do not influence the outcome of that pair, they are the exogenous variation needed for an unbiased estimation.

Assumptions

Two distinct groups pair up – the startups and the joiners. Each joiner can only be hired by one startup in a given market while startups can only hire a given quota of joiners. The quota is the number of joiners hired in a year by a given startup and it is assumed that each startup uses up its quota. These two groups pair up in a defined market. In this study, a market is defined as an industry-year-state entity. In each market, each group has complete information on the existence and characteristics of each entity in the other group. It is also assumed that the outcome of the match, the joiners' earnings one year after joining, is only determined by characteristics of the startup, joiner and economic controls. In other words, there is no other transfer among parties. Joiners cannot trade lower earnings against a startup higher in the ranking, whereas startups cannot trade better joiners for higher earnings.

Equations

M_{ij} =I(startup i hires joiner j)

$R_i=T_i\beta+n_i$

$R_j=J_j\gamma+d_j$

$\text{Ln earnings}_{ij} = \alpha_0+ T_i\alpha_1+J_j\alpha_2+C_{ij}\alpha_3+e_{ij}$

Where M_{ij} =1 when the startup i pairs up with the joiner j based on the equilibrium obtained from R_i and R_j, the respective startup and joiner rankings. T represents the vector of the startup and founding team characteristics; J represents the vector of the joiner characteristics; and C represents the vector of controls. All the error terms, n_i d_j e_{ij}, are normally distributed.

Equilibrium

A joiner j prefers a firm i if and only if $R_i > R_{i'}$ $\forall$ $i \neq i'$. Conversely, a startup i prefers a joiner j if and only if $R_j > R_{j'}$. Each R_i and R_j are distinct and thus, there is no tie. A stable equilibrium is reached if there is no blocking pair, so no agent has an incentive to deviate. In other words, the equilibrium is stable if the worst employee of a startup is better off with that startup than with any worse startup. Of course, this employee would be better off with a better startup but that startup has no incentive to hire this employee because that startup can hire better employees. Conversely, the equilibrium is stable if a startup is better off with its worst employee rather than with the best employee of the startup ranked right after.

Research on college admission proves that stable equilibria are reached with pair-wise stability. My model is a specific case that produces a unique equilibrium needed for empirical estimation. The unique equilibrium is based on group stability that has been proven to be equivalent to pair-wise stability by Roth and Sotomayor (1989). My study uses Chen (2013) who derived the bound and lower bound of ranking and proved the existence of a unique equilibrium. For the formal proof, please check Chen (2013).

Estimation

The two-sided matching estimation can be challenging. To use a maximum likelihood estimation, I would have to obtain the likelihood function by integrating the joint density of the endogeneous variables and the latent rankings conditional on the exogeneous variables and the parameters: p (M_{ij}, Ln $earnings_{ij}$, R_i, R_j / X, α, β, γ, κ, λ, σ^2_v). This integration over a large number of dimensions, basically the ranking of each agent, is challenging. Further, as the ranking of each agent depends on the ranking of all the other agents, the integration cannot be factored into product of lower dimensions (Chen, 2013). Therefore, a simple integration of the likelihood function is not possible. Instead, a solution was developed using the Bernstein-von Mises theorem that states that the mean of Bayesian posterior distribution has the same sampling asympottic distribution as the one obtained from maximum likelihood estimation (Doob, 1949; Freedmand, 1963, 1965). The solution consists of a Bayesian estimation with data augmentation and Gibbs sampling (Gelfand and Smith, 1990; Geweke, 1999). Because it is still difficult to draw directly from a joint density, Gibbs sampling is used to draw on the conditional density of each variable given the value of the others. Data augmentation means that the latent variables, the rankings, are treated as parameters. Thus, the difficult integration problem has been converted into a simulation exercise (Sørensen, 2007; Park, 2013; Chen, 2013). In each iteration, each parameter is simulated conditional on all the other parameters and the simulated distribution converges to the conditional posterior distribution under weak regularity conditions (Roberts & Smith, 1994). Conditional posterior distributions are obtained from the upper and lower bounds of the rankings and Bayes probability law. For the full derivation, please also check Chen (2013). In this estimation, I use 20,000 draws; the first ten percent of the draws are discarded for burn-in. The coefficients of the variables are the mean of these variables across the 18,000 draws. The standard deviations are also computed across the 18,000 draws.

Error terms and prior distributions

To allow correlation among the error terms, the relationship is set as:

$e_{ij}=\kappa\, n_i + \lambda\, d_j + \nu_{ij}$, $\nu_{ij} \sim N(0, \sigma^2_\nu)$

The signs of the model are identified by requiring that λ to be positive as joiners with higher unobserved ranking position obtain higher earnings. The prior distributions are multivariate normal for α, β and γ, normal for κ, and truncated normal for λ (truncated on the left at zero). I choose uninformative priors with a mean of 0 and a variance of 10 following prior research (Sørensen, 2007; Park, 2013; Chen, 2013). The prior distribution of $1/\sigma^2_\nu$ is gamma G (2, 1).

Data source

I use two confidential datasets from the US Census Bureau: the Longitudinal Employer Household Dynamics (hereafter, LEHD); and the Longitudinal Business Dynamics bridge (hereafter, LBD). The LEHD is built from the unemployment insurance that employers have to report by law. The LEHD covers 30 states starting in 1991 until 2008. It contains individual level information such as quarterly earnings, age, gender, race, education and citizenship; establishment level information such as industry, state, county, number of employees and total payroll; and the employee-employer link for every quarter. The LBD bridge connects the establishment id to the firm id at the national level and, thus, allows checking whether a new establishment is also a new firm.

Startup sample

As explained in more details in Essay 1, I extracted a sample from the LEHD of around 6,000 startups created between 2000 and 2006 in 18 states and five 3-digit NAICS. I choose these 18 states because their time coverage started at the latest in 1995 and I need a few years to build my experience measures before the creation of the startups. I focus on the following five industries because they are technological while providing clear employment relationships: Fabricated Metal Product Manufacturing; Machinery Manufacturing; Computer and Electronic Product Manufacturing; Electrical Equipment, Appliance, and Component Manufacturing; and Transportation Equipment Manufacturing. From these 6,000 startups, around 1,000 startups were kept as the sample of this essay. Were selected the startups that survived more than a year (i.e. at least until their 6th quarter) and hired at least one joiner between their 6th quarter and their 16th quarter. As I want to compare startups in the same age range, I also narrow the observation time span from 2003 to 2007. For each year, the pool of startups is made out of firms that are between 1 year and 3 years old.

Joiner sample

A joiner is an individual who decided to leave his/her job to join a startup at an early stage (after the startup's 1st year and before its 4th year, so between the startup's 6th and 16th quarters) and exercised a managerial position in a firm the year before joining the startup. Because the LEHD is a census of all types of workers including part-time workers and workers with multiple jobs, the sample has to be trimmed to only include workers who are integrally part of the labor market and for whom matching to a specific job economically matters. To determine the cutoff, I use the minimum earnings among the average yearly earnings of the most common managerial jobs in the five industries based on the publicly available data of the Bureau of Labor Statistics. These yearly earnings were $52,000 in 2008 for a first line supervisor/manager of production and operating workers in electric equipment manufacturing[9]. To summarize, from all the workers who joined a startup between its first and third year, I only retain joiners who earned at least $52,000 the year before joining. From this pool, I only retain joiners who worked exclusively for at least one year in the startups. The total number of joiners is around 4,000.

Markets

While markets are not observed in the results, they serve to structure the dataset. A market is defined as a state-industry-year entity in which startups and joiners pair up. Structured this way, the dataset is made up of 110,000 dyads, which represent any combination between a startup and a joiner in a market. By comparison, if there was no market structure, all the startups could pair up with all the joiners and the total number of dyads would be 1,000x4,000=4,000,000. This would not make economic sense as the joiners are not permanently on the job market for five years across all states and all industries. The division of the labor market by state, industry, and year seems a reasonable option. Ninety-five percent of the labor force that switches jobs within a year remains in the same state (Molloy et al., 2011). Further, individuals who change jobs while being employed at a supervision-level job the year before are expected to have a good idea of the industry in which they want to work. As for the year, it is a convenient

[9] http://www.bls.gov/iag/tgs/iag335.htm#earnings – converted into 2008-dollar value

time period for the estimation because shorter time periods such as quarters would not have enough hiring events and the variance across observations would not be meaningful. The studied years are from 2003 to 2007. For each year, startups that are between 1 year and 3 years pair up with joiners. Around 120 markets are created which means that on average a market consists of around 900 dyads of 60 joiners and around 15 startups. These average numbers suggest that the assumption about complete information in a given market is reasonable.

Dependent variables

In the matching, M_{ij} =1 when the startup i pairs up with the joiner j. Every joiner is matched once and only once, while every startup is matched at least once.

In the performance equation, following research on individual performance (Braguinsky et al., 2012; Parent, 2000), I used the natural logarithm of the yearly earnings of the joiner one year after they joined in the startups. The earnings include the wages, bonuses and exercised stock options obtained during their job in the startups.

Independent variables

The startup variables and joiner variables are conceptually the same but they are measured over different time periods (see Figures 1 and 2). Here is an example. A startup created the first quarter of 2003 has its founding team determined during its 5^{th} quarter, so the first quarter of 2004. The founding team experience variables are measured from the beginning of the LEHD up to 2002. The startup hires a joiner in the second quarter of 2004 so during its 6^{th} quarter. Thus, 2004 is the year t during which the joiner is hired. Her experience variables are measured from her first appearance in the LEHD, most likely in the 1990s up to 2003 while her performance is measured in year t+1, 2005. As the time period of measurement is clarified, I describe the variables at the individual level. The founding team variables are the averages of the founding team members' variables.

Figure 4.1 Startup timeline

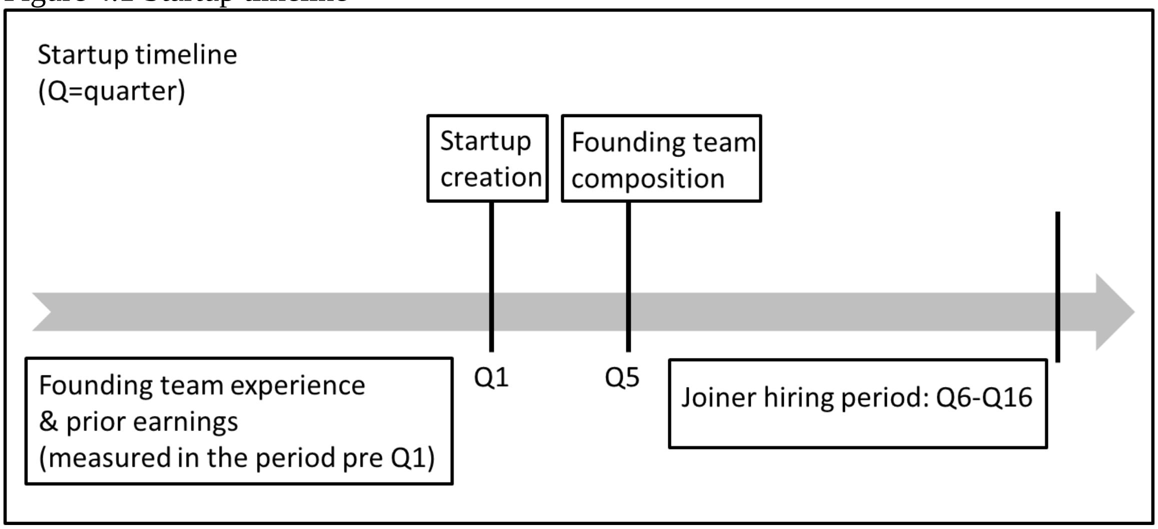
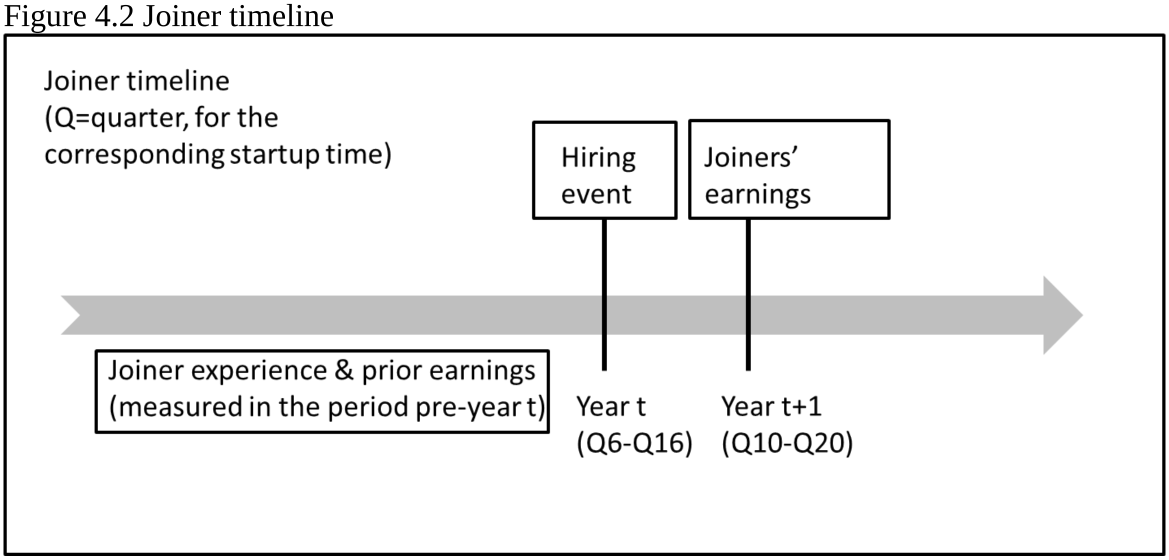


Figure 4.2 Joiner timeline



Experience variables **–** Target industry experience relates to the industry knowledge an individual acquires through work experience in the industry of the startup (e.g. Delmar & Shane, 2006) and is first measured as the number of years an employee worked in the 3-digit NAICS industry of the startup before being hired in the startup. I then break down the variable into five dummy variables because the relationship was not linear. I choose the dummies so that their interpretation makes sense and their sizes in number of observations are balanced. The five dummies are the following: zero year of target industry experience; more than zero but less than or equal to 2 years; more than 2 but less than or equal to 4 years; more than 4 but less than or equal to 6 years; and strictly more than 6 years. The omitted variable is the zero year of target industry experience. For the joiners, the tails of the distribution are heavier while for the founding teams they are lighter[10]. Entrepreneurial experience relates to the entrepreneurial knowledge an individual acquires and is measured by the number of times an employee was part of the founding team of a startup, i.e. was employed the first year the startup was created (e.g. Delmar & Shane, 2006; Shane & Stuart, 2002). Age is a proxy for the time an individual acquires general experience and is exposed to the labor market (Jovanovic, 1979). Because the relationship was not linear, it is also broken down in four dummies: less than thirty years; more than thirty but less than 40 years; more than 40 but less than fifty years; and more than fifty years.

***Productivity, ability and potential variables* –** Education signals the productivity of a worker (Spence, 1973) and is measured by a college dummy, which is coded 1 when the worker has reached at least 16 years of education (6 years of elementary school, 6 years of high school and 4 years of college) and 0 otherwise. Graduate studies are

[10] The number of observations per dummy cannot be disclosed.

captured in the same dummy. Prior earnings variable relates to the general ability of a worker and is measured by the annual earnings of the worker the year before he or she is hired by the startups (Agarwal et al., 2013; Braguinsky et al., 2012). Team size relates to the size of the entrepreneurial opportunity and is measured by the number of founding team members who are the number of employees of the startups at its 5^{th} quarter. To be included, they had to have earned at least $ 10,000 yearly over their career.

Demographic variables – Gender is coded 1 if the worker is a male and 0 otherwise. Race is coded 1 if the worker is white and 0 otherwise. An alien is coded 1 if the worker is not a US citizen and 0 otherwise.

Results

Table 4.1 presents the descriptive statistics of the team and joiner variables as well at the t-test results. The average founding team size is eight team members with a large standard deviation of almost seven team members. The founding teams' average target industry experience is 1.84 years and is significantly lower than the joiners' average target industry experience, which is around 3 years. Their average ages are also significantly different – 39.48 years for the founders and 41.60 for the joiners. The founding teams' and joiners' entrepreneurial experience is similar and around .5. Because the sample only includes joiners who earned at least $52,000 before joining, their prior earnings are significantly higher than the founding team members' ones – $90,732 versus $43,004. For this same reason, it is also important to compare the ability based on earnings within each group and not across groups. The demographic characteristics are along the same lines but on average, joiners have slightly higher percentages than founding teams, which turn into significant differences. Thirty percent of the joiners have a college degree while only twenty-one percent of the founding team members do. The percentage of male, white and alien joiners are also higher. In terms of gender and race, joiners are more often coming from the majority group whereas in terms of citizenship, it is the opposite. Finally, it is also interesting to note that the year before joining, joiners earned on average $90,732 while one year into their startup job, their earnings decrease on average to $72,510.

Table 4.1 Descriptive statistics for the startups and joiners with t-test

Start-up (n=1000)	**Mean**	**Std. dev.**	**Joiner (n=4000)**	**Mean**	**Std. dev.**	**t-statistics**	**p-value**
Team size	7.83	6.51	Joiner's earnings$_{t+1}$ (log)	11.19	0.83	NA	
Av. target ind. exp.	1.84	2.27	Target ind. exp.	3.06	4.21	-12.43	***
Av. age	39.48	6.56	Age	41.60	9.52	-8.33	***
Team average # of entrepreneurial exp.	0.49	0.55	Average # of entrepreneurial exp.	0.49	0.90	-0.12	
Team's average earnings$_{t-1}$ (log)	10.67	0.73	Earnings$_{t-1}$ (log)	11.42	0.49	-31.58	***
Share of college-educated team members	0.21	0.20	College degree	0.31	0.46	-9.94	***
Share of male team member	0.80	0.21	Gender	0.87	0.34	-7.25	***
Share of white	0.66	0.32	White	0.69	0.46	-2.23	***
Share of aliens	0.20	0.26	Alien	0.22	0.41	-1.52	^
Number of new establishments in the startup county (log)	8.93	1.83					

^ significant at 10% one-sided test; *, **, *** significant at 10%, 5% and 1% two-sided test.

Table 4.2 presents the results of the mutual selection equation of the matching model. The mutual selection between the two parties is determined by their ranking position. The higher the rank of a party, the most attractive this party is to its potential counterpart. On the startup side, large founding teams are more attractive. Larger teams signal to the joiners a bigger opportunity or an opportunity with higher potential. The level of education is positive and significant as well. This signals the productivity of the team members to the joiners. As developed in the theory, it also signals that the team can connect to scientific knowledge to develop more advanced innovation. The average prior earnings are not significant. Nor is target industry experience or entrepreneurial experience significant. One of the age categories, average age between forty and fifty years old, is less attractive than teams younger than thirty years old. Two of the three demographic characteristics turn out negative and significant: the share of aliens on the team; and the share of white team members. In other words, teams with fewer aliens and fewer white team members are more attractive.

On the joiner side, the target industry experience is the most significant characteristic that makes a joiner attractive. This is in line with prior work showing that industry knowledge is important for success at the startup level (Agarwal et al., 2004) and at the individual level (Parent, 2000). The second most important characteristic is the joiner's gender. Male hires are significantly preferred. Joiners with college education and age between thirty and forty years are also positive but weakly significant.

The interpretation becomes richer when examining startups and joiners' coefficients side-by-side and when computing the probability advantage from their coefficients[11]. This probability advantage represents the probability of a given agent to be chosen over another agent. Founding teams with target industry experience are not significantly more attractive than founding teams without target industry experience Joiners with target industry experience of three and four years and more than six years are significantly more attractive than joiners with no target industry experience. These findings are partially consistent with prior work on target industry experience. Joiners with three to four years, joiners with five to six years and joiners with more than six years of target industry experience have respectively a probability advantage over joiners with no such experience of 7.43%, 4.66% and 6.85%. Entrepreneurial experience is significant for neither side. Joiners who obtained a college degree have a probability advantage of 2.80% over joiners who did not. An increase in the share of college-educated teammates of a standard deviation (20%) gives a probability advantage of 3.68%. The prior earnings of the founding teams and joiners are insignificant. Finally, The effect of on large teams is positive and significant at 10%. A founding team that increases of around seven team members has a probability advantage of 3.10%. The effect of age on the selection differs for the joiners and founding teams. Joiners between thirty and forty years old are more attractive than joiners less than thirty years old. This translates into a probability advantage of 4.85% over joiners who are less than thirty years old. In comparison, founding teams between forty-one and fifty years old have a probability disadvantage of 12.96% over teams less than thirty years old. Young founding teams are clearly more attractive to joiners. The other age categories are not significantly different from being

[11] The probability advantage is computed as follow: 2*[normal cumulative distribution function ($X_i\beta$-$X_{i'}\beta$)]-1 $\forall$ i$\neq$ i'

less than thirty. These age results are in line with the target industry experience results – age as a proxy for general experience makes joiners more attractive while it is detrimental for founding teams.

Put together, the demographic characteristics could seem puzzling. First, founding teams with high share of aliens are at a disadvantage – increasing this share by one standard deviation (26%) put them at a disadvantage of 6.77%. Increasing the share of white people by one standard deviation (32%) also put the startups at a disadvantage of 3.73 %. For joiners, gender has a significant impact – being a male gives an advantage of 5.59% over being a female. Clearly, there is a mismatch in the demographic characteristics that does not suggest homophily. The positive results of being a US citizen and a male can be interpreted in the light of being part of the majority and having more connections to stakeholders in the industry as suggested by the research on social capital disparities (Lin, 2000). As for the share of non-white, it might signal ability if it is more difficult for minorities to be selected in this type of labor market.

Table 4.2 Matching model for selection

Variables	Mean	Std. dev.		Probability advantage
Start-up				
Team size	0.0078	0.0047	*	3.10
Av. target ind. exp. (>0 & <=2 years)	0.0433	0.0792		2.44
Av. target ind. exp. (>2 & <=4 years)	0.0563	0.0944		3.17
Av. target ind. exp.(>4 & <=6 years)	0.1059	0.1120		5.97
Av. target ind. exp. (>6 years)	0.1601	0.1362		9.01
Av. age (>=30 and <41 years)	-0.1017	0.1307		-5.73
Av. age (>=41 and <51 years)	-0.2308	0.1372	*	-12.96
Av. age (>=51 years)	-0.2073	0.1870		-11.66
Team average # of entrepreneurial exp.	0.0089	0.0598		0.28
Team's average earnings$_{t-1}$ (log)	0.0056	0.0240		0.23
Share of college-educated team members	0.3262	0.1554	**	3.68
Share of male team member	0.1366	0.1462		1.65
Share of white	-0.2048	0.1351	^	-3.73
Share of aliens	-0.4555	0.1599	***	-6.77
Joiner				
Target ind. exp. (>0 & <=2 years)	-0.0024	0.0602		-0.14
Target ind. exp. (>2 & <=4 years)	0.1318	0.0643	**	7.43
Target ind. exp. (>4 & <=6 years)	0.0826	0.0650		4.66
Target ind. exp. (>6 years)	0.1216	0.0491	**	6.85
Age (>=30 and <41 years)	0.0861	0.0659	^	4.85
Age (>=41 and <51 years)	0.0400	0.0678		2.26
Age (>=51 years)	0.0569	0.0747		3.21
Average # of entrepreneurial exp.	0.0030	0.0202		0.15
Earnings$_{t-1}$ (log)	-0.0090	0.0079		-0.25
College degree	0.0497	0.0386	^	2.80
Gender	0.0992	0.0522	*	5.59
White	-0.0545	0.0465		-3.08
Alien	-0.0166	0.0513		-0.94
Number of observations	110000			

For continuous variables, the probability advantage is computed with an increase of one standard deviation. For dummy variable, it is computed with the dummy being one and is interpreted in comparison to the omitted category. ^ significant at 10% one-sided test *, **, *** significant at 10%, 5% and 1% two-sided test.

Table 4.3 presents the performance results. Once selection has been accounted for, the earnings of the joiner is positively affected by the earnings in t-1 of the joiner and of the founding team, being male and being white. Earnings prior to the startup time are the most significant factors affecting the earnings of the joiners in t+1. An increase of 10% of the joiners' prior earnings lead to an increase of 4.7% of the joiners' earnings and an increase of 10% of the founding team prior earnings lead to an increase of 1.7% of the joiners' earnings. The marginal effects may seem small but on average joiners earn less in the startup and so, these small effects are not surprising. The marginal effects of the gender and race are more striking. A male joiner earns 23.66% more than a female joiner and a white joiner earns 16% more than a non-white joiner[12].

Even when becoming entrepreneurs, founding team members organize a pay system that is in line with what they earned before. Joiners who leave an incumbent firm for entrepreneurship still can expect to obtain earnings that are proportional to what they earned before. Beyond the monetary similarities, these results also suggest that a signal of general ability, high earnings, is what mainly affects the joiners' performance. More specific knowledge acquired through experience has no effect. Because the experience variables are insignificant on the founding team side as well as on the joiner side, it also suggest that the combination of experiences does not create additional value that can be directly reflected in the earnings of the joiner. Being white and male positively affects the earnings as well, which shows that earnings structure and disparities based on race and gender are also present in the context of technological startups.

Kappa, Lambda and sigma are the coefficients that explain the relationship between the error term in the earnings regression and the error terms in the selection rankings. Kappa is insignificant, which means that the unobserved startup characteristics do not significantly affect the error term of the earnings regression. Lambda is weakly significant meaning that unobserved joiner characteristics affect both the joiners'

[12] Marginal effect for dummy variables computed as follow: $100x(e^{\gamma}-1)$

selection and their earnings. Sigma square, the variance of the residuals of the error term is also significant, meaning that other factors outside the selection still affect the earnings. Overall, it means that the unobserved characteristics of the startups is a not a source of endogeneity in the earnings while the unobserved characteristics of the joiners that affect their selection also affect their earnings, justifying the use of the sorting at least in the joiners pool as an exogenous variation in the earnings regression.

For comparison between the matching model and discrete choice model and linear regression, I report two additional tables in the appendix. Table A3 presents the results from a logit regression of the match variables on the startups' and joiners' characteristics, and the market dummies. It is interesting to note that the logit reveals similar effect of startup characteristics on the matching but fail to reveal the joiners' characteristics. Table A4 presents the linear regression of the joiners' earnings on the startups' and joiners' characteristics. The coefficients with the largest effects are, as in the matching model, prior earnings and being a white male. However, many other characteristics are significant suggesting that in this regression the effect of these characteristics on selection and on earnings are confounded.

Table 4.3 Matching model for outcome (log earningst+1)

Variables	Mean	Std. dev.	
Startup			
Constant	3.12	1.17	***
Team size	0.01	0.01	
Av. target ind. exp. (>0 & <=2 years)	0.05	0.12	
Av. target ind. exp. (>2 & <=4 years)	-0.02	0.14	
Av. target ind. exp.(>4 & <=6 years)	0.00	0.16	
Av. target ind. exp. (>6 years)	-0.09	0.20	
Av. age (>=30 and <41 years)	0.13	0.23	
Av. age (>=41 and <51 years)	0.10	0.24	
Av. age (>=51 years)	0.15	0.31	
Team average # of entrepreneurial exp.	-0.08	0.09	
Team's average earnings$_{t-1}$ (log)	0.17	0.07	**
Share of college-educated team members	0.19	0.22	
Share of male team member	0.04	0.22	
Share of white	0.01	0.20	
Share of aliens	0.06	0.25	
Joiner			
Taregt ind. exp. (>0 & <=2 years)	0.10	0.14	
Target ind. exp. (>2 & <=4 years)	0.12	0.15	
Target ind. exp. (>4 & <=6 years)	0.12	0.15	
Target ind. exp. (>6 years)	0.08	0.12	
Age>=30 and <41	0.05	0.15	
Age>=41 and <51	0.03	0.15	
Age >=51	0.02	0.17	
Average # of entrepreneurial exp.	0.03	0.04	
Earnings$_{t-1}$ (log)	0.47	0.09	***
College degree	0.06	0.09	
Gender	0.21	0.12	*
White	0.15	0.11	^
Alien	0.04	0.12	
Controls			
# new establishments in the startup county (log)	-0.01	0.03	
year dummies	Included		
region dummies	Included		
industry dummies	Included		
Kappa	-0.04	0.06	
Lambda	0.06	0.04	^
Sigma square	0.06	0.00	***
Number of observations	4000		

^ significant at 10% one-sided test *, **, *** significant at 10%, 5% and 1% two-sided test.

DISCUSSION

While human capital is crucial for startups' survival and growth, little is known about the acquisition of talents by startups. This essay uses a matching model to identify what startups' and joiners' characteristics affect their mutual selection on the labor market. I find that startups whose founding teams can signal productivity and growth potential are the top choice of joiners. Joiners who are male and can signal target industry experience and, to a lesser extent, productivity, are the top choice of startups. These results are important because they do not completely support the expectations that come from prior research on startup. Startups with target industry experience or general experience captured by age might perform better (e.g. Delmar & Shane, 2006) but this does not necessarily imply that they can hire the best joiners. Also, startups with prior entrepreneurial experience might be able to attract investors (e.g. Shane & Stuart, 2002) but not the best joiners. By contrast, relatively straightforward characteristics, size and education, are the key signals that attract joiners. On the joiners' side, as expected, joiners with target industry experience are more attractive potential hires. Target industry experience of three years and more gives joiners a consequent advantage to be picked by good startups over joiners with no target industry experience. More surprisingly, being a male is the second characteristic that helps joiners being selected and gives them a consequent advantage over their female counterpart. While prior work on gender differences in entrepreneurship has focused on access to funding (Brush et al., 2014), this result sheds light on the access to entrepreneurial jobs and clearly shows that male joiners also have a consequential advantage over women. This fuels the current debate on whether startups are a favorable work place for women (Khazan, 2015).

I do not find support for homophily based on ascribed demographic characteristics such as gender, race and citizenship. This contrasts with work on team formation that found that homophily was one of the key drivers of mutual selection (Ruef et al., 2003). Two factors might explain this difference: the startup stage and the context. The startups in this sample are past the founding stage where entrepreneurs might only have a very limited pool of individuals they can choose from. Second, this study is based on a sample of technological startups for which experience and productivity might matter more. Instead of a homophilic pattern, the results suggest that startups and joiners might be preferred because they are part of the dominating majorities, respectively, US citizens and male, which relates to higher status and more connections (Li, 2000). The founding team's US citizenship decreases also the uncertainty regarding the future of the startup in comparison to founders with temporary work permits. However, startups with fewer white members are also preferred, which there could suggest that on average individuals from minorities who are able to "make it" might be of higher ability.

Controlling for the mutual selection, I investigate the effect of startups' and joiners' characteristics on the earnings of the joiners one year after they joined the startup. I find that their ability, gender and race, as well as the ability of the founding team affect their earnings. Ability trumps any other factors such as experience. In other words, what gets joiners a job (e.g. experience) is not what affects their earnings. First, one has to expect that prior earnings that capture ability would be the main factor affecting earnings in the startup. Second, the fact that the combination of the founding teams' and joiners' experiences has no influence suggest that either the combination has not played out (yet) to be reflected in the earnings or that value created from this combination is not reflected in the joiners' earnings. In this latter case, the startups might be the ones appropriating this value. After all, in the context of technological manufacturing industries, the startups and their founding teams own most of the tangible and intangible complementary assets that affect value appropriation (Teece, 1986; Campbell et al., 2012). Besides prior earnings, the two other factors that positively affect the joiners' earnings in the startups are being male and white. These two results suggest that earnings disparities based on gender and race exist in the startup environment.

Limitations and future research

The strength of this matching model is to present clear and concise results to explain a two-sided selection. In this regard, it surpasses the use of a discrete choice model. However, the matching model, like discrete choice models, has to rest rely on a few strong assumptions, especially concerning the pool of available choices the agents consider. The models do not take into account the stage where startups and joiners have to identify their potential counterparts. As researchers, we make the assumption that the agents know all their possible choices and consider all of them. In this context, it means that joiners know all the startups who are hiring in their market, a given state, industry, year. Similarly, the startups know all the joiners they could potentially hire. Because this study focuses on a specific segment of the labor market of small size (i.e on average, sixty joiners and fifteen startups per market), the assumption is reasonable. Still, this assumption opens up opportunities for future research that could use personal networks to define the pool of potential counterparts (Granovetter, 1981). This future research would be relevant on even more specific labor markets such as the Silicon Valley.

The second assumption is that all the agents have the same view of what determines the best counterpart. In that sense, the ranking that leads to the selection is absolute. Every agent shares the same ranking. This relies on the fact that all the startups and joiners want to maximize the same type of performance for which a best counterpart exists. While this assumption seems strong, it does not prevent the identification of important general characteristics such as experience, education and gender on the labor market. To study choices based on expectation to realize specific outcome, more specific characteristics might be needed as well as a model that allows flexibility in the ranking. An example could be pharmaceutical firms having different strategy to enter a new therapeutic class and therefore, looking for pairing up with partners with different resources and know-how.

The third assumption of this matching model is that there is no transfer allowed between joiners and startups to potentially work with a better counterpart than what the ranking would allow them to obtain. In other words, the assumption is that all the agents would only pair up with the best agent they could get and not with a lower ranked agent who can offer higher pay or who would accept lower pay. This offers an opportunity for future research to use matching models with transfer and datasets with ownership information to better capture the startup hiring process. Doing so will also help identify how much of the value is appropriated by the founding team and by the joiners.

Regarding the data, the use of US Census data permits me to cover all the startups of a given industry in a given time period. This increases the generalization of the results but comes with the trade-off of missing fine-grained information. Future research can collect more information on the occupations and functional background to capture a richer phenomenon of human capital building in startups (Beckman & Burton, 2008).

Theoretical implications

Prior studies on pre-founding work experience extensively shows that this pre-founding experience in the target industry or industry of the startup is positively associated with startup performance (Eisenhardt & Schoohoven, 1990; Agarwal et al., 2004; Delmar & Shane, 2006; Chatterji, 2009). It is unclear, however, whether startups without target industry experience could invert the trend. This essay does not directly test if the acquisition of talent inverts the trend but shows that startups with high ability and potential signals can acquire talent with target industry experience regardless of their own experience.

Prior studies on entrepreneurial team formation and team member addition found that homophily affects mutual selection. Similar patterns were not found in this essay. There are multiple reasons to this. A few of these studies relied on interviews and case studies in very specific contexts such as academic startups (Clarysse & Moray, 2004; Forbes et al., 2006) and family businesses (Discua Cruz et al., 2012). The empirical studies used samples representative of the US and UK economies (Ucbasaran et al. 2003; Ruef et al., 2003), which include business for which prior experience or education might not be as critical. As the context in which the entrepreneurs evolve influences the team formation (Aldrich & Kim, 2007), by studying technological industries, I find different results that suggest that more might have to be uncovered in the team formation field.

Prior research in entrepreneurship and strategy explained phenomena by focus on the characteristics of one of the actors. This essay contributes to the emerging research that focuses on understanding choices as mutual selection (Mindruta, 2013; Mindruta et al., 2014). This essay also expands the use of matching models to explain mutual selection and the resulting outcome (Chen, 2013; Sørensen, 2007).

Speaking of outcome, prior research studied entrepreneurs' earnings (Braguinsky et al., 2012; Campbell, 2013). However, little is known on the characteristics that influence earnings of workers joining startups. This essay fills this gap while addressing the inherent endogeneity issue due to hiring decisions. The results show that controlling for selection, prior earnings of the joiners and of the founding team, as well as gender and race, are the main drivers of joiners' earnings in a startup. While contributing to entrepreneurship research, this result also connects with prior work in labor economics and sociology on the weight of prior earnings structure and disparities (Altonji & Blank, 1999; McCall, 2001). Despite their new and more dynamic environment, startups set up remuneration system conducive to disparities.

Practical implications

This research has practical implications for startups and potential joiners as well as for policy makers. As for startups, it informs them about potential strategies in hiring talented individuals. More specifically, to appear as an attractive employer, startups have to signal ability and potential rather than extensive experience. Similarly, for joiners, this research helps them understand what characteristics make them attractive for startups and what characteristics will affect their earnings. Joiners have the difficult task of signaling both target industry experience and productivity to attract promising startups. In an ideal case, potential joiners would build their experience in incumbent firms where they do not extensively trade earnings to acquire this experience because their earnings in the startup are based on the earnings gained in the incumbent firm.

This research informs policy makers of two characteristics to develop to create an attractive labor force for startups: education and experience in the target industry. In other words, policies that facilitate access to college education and internships in technological industries should be beneficial for startups. Two ascribed characteristics also affect the attractiveness of the labor force for startups: being a male; and being between 30 and 40 years old. Ideally, policy makers should decrease the effect of these two characteristics to limit discrimination. This research also suggests that gender and race disparities affect the startups employees' earnings. As more and more attention is drawn to discrimination and disparities mainly based on gender in startups (Khazan, 2015), policy makers should foster specific studies in the context of startups and develop solutions.

CHAPTER 5
CONCLUSION

The goal of my dissertation is to understand how startups' initial endowment in human capital affects their performance and subsequent acquisition of human capital. My dissertation relies on the study of the startup founding team and on individual team members providing a framework where the two levels of analysis interact.

The first essay shows that founding teams with prior shared experience benefit from the inclusion of job hoppers in the team. Job hoppers are individuals who embody diverse experience through their multiple job moves over a recent time period. Startup performance is positively associated with the interaction of prior shared experience and job hoppers when the prior shared experience is of at least three years. Using previous work on startups' human capital and pre-entry experience, I categorize the prior shared experience and the job hoppers' experience as being acquired in the target industry or outside the target industry. In this configuration, I find that startups with prior shared experience in target industry benefit from job hoppers who worked outside the target industry. I also find that startups with prior shared experience outside the target industry benefit from job hoppers who worked in the target industry. These two effects are positive when the prior shared experiences are of two years or more. I also show that a teammate who did not hop but brought the same industry experience as a job hopper does not lead to the same positive results. This suggests that job hoppers are unique due to their diverse experience at two levels: across firms; and from an industry different than the rest of the team. This unique characteristic allows them to create constructive disruption and innovation through recombination. These results underscore specific complementarities that underlie the effect of the broader concept of diverse experience on performance.

The second essay highlights which startups' and joiners' characteristics affect their mutual selection on the labor market. Joiners are individuals who want to work in startups in their early stage but who do not want to be a founder. This essay is based on an assortative matching methodology. Partners at the top of their own ranking are more attractive and are likely to match up first. In other words, the best startups are going to match up with the best joiners. The model reveals the characteristics that define the rank of the startups and joiners. I find that startups with younger founding teams that can signal higher productivity with their level of education and higher growth potential with the initial founding team size are preferred. I also find that male joiners with target industry experience of three years or more and with a college degree are preferred. Further, startups with a majority of non-white team members and of US citizens are preferred. This mismatch of demographic characteristics does not suggest that homophily is playing out. On the other hand, it suggests that these two demographic characteristics might proxy for other attributes such as higher efforts to overcome barriers to employment (workers of color) or broader connections to a majority of the industry players (US citizens and males). Using the sorting in the selection as an instrument, I then analyze the impact of the same characteristics on the joiners' earnings. I find that joiners' earnings obtained from the startup one year later is mainly influenced by the founding team's signal of ability, the joiners' signal of ability, both measured by prior earnings, and the joiners' gender and race. Interestingly, the experience variables do not have a remaining effect after their effect has been taken into account in the selection stage. This underscores the fact that target industry experience provides joiners with a high-ranked employer but does not directly affect their performance in the startup. This also underscores that earnings structure is mainly carried over from established firms to startups but also, include gender and race disparities that are more salient in the startup than in established firms.

When comparing both essays, it is interesting to note that two results are clearly aligned while two others are not. I start the discussion with the former two. Founding teams with prior shared experience in the start-up industry perform better and joiners with target industry experience are seen as attractive partners. These two results are aligned and suggest that startups know the advantages of target industry experience and seek it. Second, a team with college educated team members is clearly a strength. College educated teams survive longer, attract better joiners and joiners with college degree also attract better startups to a smaller extent in their case. However, two results are also opposed. Start-ups with prior shared experience in the target industry survive longer but this feature does not attract better joiners. Joiners, especially the ones that I study who already achieved a relatively high position in their prior job, might be looking for a challenge and a high growth potential rather that for a startup who is likely to survive. Further, if the top-ranked joiners already have target industry experience, they might on average be indifferent in joining a firm who has some of that experience. Some joiners might prefer it to become an effective team member faster although some might look for learning opportunities in a team that has none or little of that experience. Also, there might be some latent status effect that are not directly observed but picked up by the team size, education or age. For instance, a joiner might want to work for Stanford graduates who might invent the next fastest processors rather than for a team of experienced workers coming from a mid-sized company whose careers are mainly behind them. Second, one important demographic characteristic is not aligned – the share of males is negatively associated with survival in the first essay although startups still prefer to hire male joiners. One can first speculate about the reason why gender affects survival – startups with female team members might envisage different opportunities, think through more options, take fewer risks. No matter the reasons, the difference between the two essays suggests again that there might a gender bias.

CONTRIBUTIONS

Both essays are built on the same central concept, the target industry experience of the founding teams, and, thus, both contribute to the spinout literature. The first essay highlights a cause of the performance heterogeneity among startups with target industry experience (i.e spinouts). Whereas extensive work has showed the impact of experience acquired in industry incumbent on the decision to become entrepreneurs and on the startup performance, little is known on the other experiences that reside in the founder and founding teams and how these experiences could affect the startup performance as well. Further, the second essay shows that target industry experience positively influences the joiners' probability of being chosen by a startup over their competitors. However, the target industry experience of the startup does not provide it with any hiring advantage. This is an interesting finding suggesting that the performance advantage of a spinout is not reflected in its hiring. In that sense, both essays complement each other and offer a more nuanced view of the spinouts. Further, the second essay complements the discussion of team formation of the first essay by explicitly modeling the team member addition. However, due to the model limitations, it cannot completely explain team formation but only the addition of team members to an existing team.

Both essays also contribute to the study of startups relying on the census of startups in the five technological industries over a period of nine years. This allows me to obtain and present generalized results that do not depend on the type of investors or on survey designs. Both essays offer more specific contributions which I review in the following paragraphs.

By highlighting a specific source of complementarities between different experiences, my dissertation contributes to the study of experience diversity and its effect on performance. Often, having variance in the team experience is considered positive; however, the kind of variance and the source of this variance are ignored. My dissertation lifts part of the veil regarding diversity in terms of experience in different industries and multiple firms.

By studying startups' hiring with a two-sided methodology, my dissertation contributes to a better understanding of human capital acquisition in startups. In addition to the model, the context in which the phenomenon is studied also contributes to the literature on entrepreneurial team formation that mainly finds sociological constructs as drivers of individuals' selection.

By using a two-sided matching model with Bayesian estimation, my dissertation also showcases a new methodology that can be used in entrepreneurship and in strategy to better assess outcome that relies on the collaboration between two sides. As the model is used to supplement a performance equation, it also highlights the use of sorting to handle endogeneity issues when instruments are not available (Sørensen, 2007).

By studying earnings of newly hired employees in startups, the dissertation reveals that prior earnings and being male and white are the determinants of individuals' earnings in startups. This is of interest for labor economists and sociologists to further investigate whether and why startups carry over earnings structure and disparities from established firms and labor market practices. Moreover, by disentangling the individuals and firm characteristics on sorting and on earnings for a given job, the matching model complements work using panel data that can capture trend but not completely rule out endogeneity (Parent, 2000).

IMPLICATIONS

My dissertation offers implications for the startup founding teams and for individuals who are part of the team or aspire to be. When forming their initial team, founders have to balance the amount of shared and diverse knowledge. To be beneficial, the diverse knowledge has to come from job hoppers, individuals who embody this knowledge diversity. The complementarities between the founding teams' prior shared experience and the job hoppers play out given two contingencies. The team had to already have at least two to three years of prior shared experience. The job hoppers had to bring target industry experience in teams who do not have any and experience from outside the target industry in teams who acquired their shared experience in the target industry. By contrast, if the founding teams do not have any prior shared experience, they should avoid including job hoppers.

At a later stage, when startups build their human capital by hiring, the size of the team and the share of college educated team members are the key signal to which joiners look. These signals reflect size of the entrepreneurial opportunity and productivity of the team members. These findings inform startups that even if they lack target industry experience endowment, their hiring is not affected. However, not being able to exhibit these other signals affects the quality of the joiners they can hire. For joiners having industry experience, being college-educated, male, and between thirty and forty years old are key. While the last two characteristics are ascribed and so cannot be influenced, the first two are key indicators suggesting that joiners should gain experience and education before hoping to join a high-potential startup.

As the matching model highlights which characteristics make an employee more attractive on the job market, the findings can also inform policy makers on how to prepare or improve an individual's background to get a job in specific industries (i.e. technological and manufacturing) or in specific types of firms (i.e. startups). It also highlights that policy makers have to decrease the gender bias of hiring male joiners were preferred over their female colleagues. The model also shows that earnings structure and disparities were carried over from established firms and labor markets to the startup labor markets. This could inform policy makers in the debate on the glass ceiling based on gender and race.

FUTURE RESEARCH

My dissertation shows that research on entrepreneurial teams can be challenging and that methodological advances can help encompass the phenomenon. Entrepreneurial teams are voluntarily formed, which means that the formation is endogenous to each team member selecting of all the other team members. This endogenous selection affects the startups' and individuals' outcomes. The first essay tackles this team formation by controlling for the ability of each team member measured by their prior earnings. This allows controlling for a mutual selection based on ability. However, other factors such as access to specific experience might be at play as well. This connects to a second element I could not observe in this dissertation – the identification of the entrepreneurial opportunities. It is unknown whether the entrepreneurial opportunity has been identified first and the team then formed, which would add to the selection puzzle. On the other hand, the teams might be formed first and the team members might together identify an opportunity and together elaborate the pursuit of it. This would limit the selection issue. Two different methodologies can be applied by future research to tackle this puzzle. The first one relates to ethnographic work and requires the researchers to collect real time, fine-grained observations on entrepreneurial teams and their opportunity identification. Observing the process unfold would procure information on antecedents and consequences. The second methodology, by contrast, would be using a large set of secondary data and would require expanding the matching model used in essay 2. Instead of using a two-sided model, researchers would have to develop a multi-sided model where every agent chooses everyone else in a given team. In this case, the matching model could be used to study the initial team formation during which multiple founders agree to form the team.

Regarding individual performance, prior research shows that workers left their employed job to become entrepreneurs received an increase in their earnings years later than their colleagues who remained employed in an incumbent firm receive (Campbell, 2013). While this dissertation studies the performance of joiners within the startup, future research could examine whether they can reap long-term benefits from their experience. This also connects to the employee appropriation of value in startups. The LEHD dataset does not provide information regarding the share ownership of the founding team and subsequent employees. A promising avenue for future research is to better understand how much startup team members can appropriate based on their experience and based on the time they join the startup as a founder or as a joiner. The finding in essay 2 suggests that prior earnings rather than experience determine the current appropriation of a joiner in a startup. However, this finding has to be confirmed with share ownership.

My dissertation shows the effect of the inclusion of job hoppers in a founding team and highlights what characteristics make joiners more attractive partners. The departure of these job hoppers and joiners, and their subsequent performance, remain to be studied. Prior research has examined the departure of the *lead founder* and his or her replacement by a professional CEO; however, little is known about the departure of other team members (Ucbasaran et al., 2003). Job hoppers might by definition be likely to leave after a few years (Malone, 1995). Thus, it would be interesting to see whether their departure negatively affects the startup performance or whether the startups have anticipated this departure and are only moderately affected.

Although my dissertation is anchored in the entrepreneurship and strategy fields, it also opens new avenues of research for labor scholars. The matching model estimation is a tool that labor scholars can apply to understand the selection between firms and individuals with specific features or jobs (Mindruta, 2013; Sørensen, 2007). Further, the findings suggest that startups form a context where gender and to some extent, race biases might exist in hiring and remuneration. Given how these results fit in the current debate about sexism in technological industries and in startups (Khazan, 2015), the door is clearly open for more studies in this area.

Finally, two concepts that are out of the scope of my dissertation present great avenues for future research about entrepreneurial teams: the startup team members' network and their occupation or functional background. The startup team members' network could include kinship, school and prior work ties and offer an alternative to define the labor markets in which startups and joiners match up. Second, individuals and teams' occupations or functional background could enrich the knowledge argument made in both essay. This would connect the spinout literature (e.g. Agarwal et al., 2004) and the functional background literature (e.g. Beckman & Burton, 2008).

CONCLUSION

My dissertation, across both essays, emphasizes target industry experience as a central component of the effect of human capital on performance and on the acquisition of talent. However, it also demonstrates that the effect of target industry experience can play out in more sophisticated. In the first essay, founding teams with prior shared experience in the target industry benefit from the experience of job hoppers acquired outside the target industry. Conversely, founding teams with prior shared experience outside the target industry benefit from the experience of job hoppers acquired in the target industry. The complementarities are only present when one type of experience is at the team level and the other at the individual level. Further, in the second essay, startups' target industry experience does not make them attractive to the joiners. On the other hand, joiners' experience in the target industry is a crucial factor of selection. Overall, all these findings show that even if target industry experience provides an advantage to startups, startups whose main experience is not the target industry experience can still benefit from complementarities and can still attract hires with that experience.

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APPENDIX

Table A.1 Industries at three-digit (bold) and four-digit levels

Fabricated Metal Product Manufacturing
Forging and Stamping
Cutlery and Handtool Manufacturing
Architectural and Structural Metals Manufacturing
Boiler, Tank, and Shipping Container Manufacturing
Hardware Manufacturing
Spring and Wire Product Manufacturing
Machine Shops; Turned Products; and Screw, Nut, and Bolt Manufacturing
Coating, Engraving, Heat Treating, and Allied Activities
Other Fabricated Metal Product Manufacturing
Machinery Manufacturing
Agriculture, Construction, and Mining Machinery Manufacturing
Industrial Machinery Manufacturing
Commercial and Service Industry Machinery Manufacturing
Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment Manufacturing
Metalworking Machinery Manufacturing
Engine, Turbine, and Power Transmission Equipment Manufacturing
Other General Purpose Machinery Manufacturing
Computer and Electronic Product Manufacturing
Computer and Peripheral Equipment Manufacturing
Communications Equipment Manufacturing
Audio and Video Equipment Manufacturing
Semiconductor and Other Electronic Component Manufacturing
Navigational, Measuring, Electromedical, and Control Instruments Manufacturing
Manufacturing and Reproducing Magnetic and Optical Media
Electrical Equipment, Appliance, and Component Manufacturing
Electric Lighting Equipment Manufacturing
Household Appliance Manufacturing
Electrical Equipment Manufacturing
Other Electrical Equipment and Component Manufacturing
Transportation Equipment Manufacturing
Motor Vehicle Manufacturing
Motor Vehicle Body and Trailer Manufacturing
Motor Vehicle Parts Manufacturing
Aerospace Product and Parts Manufacturing
Railroad Rolling Stock Manufacturing
Ship and Boat Building
Other Transportation Equipment Manufacturing

Table A.2 LEHD coverage

State	Region	Starting year	Ending year
Maryland	South	1985	2008
Colorado	West	1990	2008
Idaho	West	1990	2008
Illinois	Midwest	1990	2008
Indiana	Midwest	1990	2008
Louisiana	South	1990	2008
Washington	West	1990	2008
Wisconsin	Midwest	1990	2008
North Carolina	South	1991	2008
California	West	1991	2008
Oregon	West	1991	2008
Florida	South	1992	2008
Montana	West	1993	2008
Georgia	South	1994	2008
Hawaii	West	1995	2008
New Mexico	West	1995	2008
Rhodes Island	Northeast	1995	2008
Texas	South	1995	2008

Table A.3 Selection between startups and joiners (logit)

Variables	Coefficient	Std. Error	
Startup			
Team size	0.02	0.01	***
Av. target ind. exp. (>0 & <=2 years)	-0.07	0.11	
Av. target ind. exp. (>2 & <=4 years)	0.04	0.12	
Av. target ind. exp.(>4 & <=6 years)	0.03	0.13	
Av. target ind. exp. (>6 years)	-0.25	0.15	*
Av. age (>=30 and <41 years)	-0.03	0.13	
Av. age (>=41 and <51 years)	-0.16	0.16	
Av. age (>=51 years)	-0.24	0.22	
Team average # of entrepreneurial exp.	-0.19	0.06	***
Team's average earnings$_{t-1}$ (log)	0.37	0.08	***
Share of college-educated team members	0.63	0.20	***
Share of male team member	0.29	0.20	^
Share of white	-0.08	0.12	
Share of aliens	-0.26	0.14	*
Joiner			
Target ind. exp. (>0 & <=2 years)	0.00	0.00	
Target ind. exp. (>2 & <=4 years)	0.00	0.00	
Target ind. exp. (>4 & <=6 years)	0.00	0.00	
Target ind. exp. (>6 years)	0.00	0.00	
Age (>=30 and <41 years)	0.00	0.00	
Age (>=41 and <51 years)	0.00	0.00	
Age (>=51 years)	0.00	0.00	
Average # of entrepreneurial exp.	0.00	0.00	
Average earnings$_{t-1}$ (log)	0.00	0.00	
College degree	0.00	0.00	
Gender	0.00	0.00	
White	0.00	0.00	
Alien	0.00	0.00	
Market dummies	Included		
Number of observations	110000		

^ significant at 10% one-sided test *, **, *** significant at 10%, 5% and 1% two-sided test.
Robust standard error clustered by market

Table A.4 Regression of the joiners' earnings in t+1 (OLS)

Variable	Coefficient	Std. error	
Startup	2.58	0.46	***
Team size	0.01	0.00	***
Av. target ind. exp. (>0 & <=2 years)	0.06	0.05	^
Av. target ind. exp. (>2 & <=4 years)	-0.01	0.06	
Av. target ind. exp.(>4 & <=6 years)	0.03	0.06	
Av. target ind. exp. (>6 years)	-0.08	0.07	
Av. age (>=30 and <41 years)	0.11	0.10	
Av. age (>=41 and <51 years)	0.08	0.11	
Av. age (>=51 years)	0.12	0.13	
Team average # of entrepreneurial exp.	-0.08	0.04	**
Team's average earnings$_{t-1}$ (log)	0.17	0.03	***
Share of college-educated team members	0.17	0.08	**
Share of male team member	0.07	0.08	
Share of white	0.04	0.07	
Share of aliens	0.02	0.07	
Joiner			
Target ind. exp. (>0 & <=2 years)	0.10	0.04	**
Target ind. exp. (>2 & <=4 years)	0.11	0.05	**
Target ind. exp. (>4 & <=6 years)	0.12	0.04	***
Target ind. exp. (>6 years)	0.06	0.04	*
Age (>=30 and <41 years)	0.04	0.04	
Age (>=41 and <51 years)	0.02	0.05	
Age (>=51 years)	0.02	0.06	
Average # of entrepreneurial exp.	0.03	0.01	**
Average earnings$_{t-1}$ (log)	0.47	0.04	***
College degree	0.06	0.02	***
Gender	0.21	0.04	***
White	0.15	0.03	***
Alien	0.03	0.03	
Controls			
# new establishments in the startup county (log)	0.05	0.01	***
Year dummies	Included		
Industry dummies	Included		
Region dummies	Included		
Number of observations	4000		

^ significant at 10% one-sided test *, **, *** significant at 10%, 5% and 1% two-sided test.
Robust standard error clustered by startup