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Entrepreneurial teams' acquisition of talent: Evidence from technology manufacturing industries using a two-sided approach

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Abstract

Research summary: One of the established findings in the spinout literature is that founders with prior industry experience assemble larger entrepreneurial teams and create better-performing startups. We examine the role of prior industry experience in the startups' next stage—its hiring of new employees. We tackle two empirical challenges—the mutual aspect of hiring and the effect of unobserved variables on employees' earnings using a two-sided matching model. Our results reveal that even firms founded by entrepreneurs without industry experience can attract new employees with such experience if the founders start with a large entrepreneurial team. Further, startups provide new hires with an earnings premium for their industry experience. Our approach illustrates the benefits of matching models over traditional regressions.

Managerial summary: Growing startups face the question of who to hire and how much to compensate the new hires. Simultaneously, prospective new hires ask which startup to join and how much their salary will be. We explore these questions using a novel method that tackles the mutual selection process. In the context of five technological manufacturing industries, we find that having industry experience within founding teams may not be necessary to attract new hires with high quality if the startup can signal its own quality through other means such as having a larger founding team. Our results indicate that startups prefer employees with industry experience for which startups offer a wage premium. Thus, employees seeking startup employment benefit from gaining industry experience prior to joining a startup.

KEYWORDS

entrepreneurial earnings, entrepreneurial hiring, prior industry experience, startups, two-sided matching model

1 | INTRODUCTION

Prior research has emphasized human capital as one of the key drivers of firm performance (Campbell, Coff, & Kryscynski, 2012). In the entrepreneurial context, scholars have emphasized the role of the founding teams' human capital and specifically, the founding team's prior experience in the industry of their venture. Such experience drives startup creation (Agarwal, Echambadi, Franco, & Sarkar, 2004; Helfat & Lieberman, 2002), founding team size and firm size (Agarwal, Campbell, Franco, & Ganco, 2016; Cooper, Woo, & Dunkelberg, 1989; Roberts, Klepper, & Hayward, 2011), and, consequently, performance (Balasubramanian & Sakakibara, 2015; Chatterji, 2009; Colombo & Grilli, 2005; Helfat & Lieberman, 2002).

While the role of the prior industry experience of the initial founding team has been broadly recognized as determining the fate of the startup, its role in the startup's next stage—the acquisition of new talent—has received significantly less attention. Similarly, whether and how firms hire and compensate employees with prior industry experience as they grow is unclear. Because growing their human capital is critical to startups' survival and growth (Beckman & Burton, 2008; Wasserman, 2012) and many individuals are interested in working for startups (Roach & Sauermann, 2015), this lack of scholarly attention to prior industry experience as startups grow is puzzling.

We address this gap by using a two-sided matching estimation to examine the role of prior industry experience in startups' acquisition of human capital. The industry experience of new hires and the founding teams is likely playing a role in the matching and earnings of the new hires. Further, prior work shows a positive relationship between a founding team's prior industry experience and its team size (Colombo & Grilli, 2005; Cooper, 1985; Roberts et al., 2011). Founders with prior industry experience have a higher chance of success, which attracts larger and better teams, and increases the startup's probability of success (Agarwal et al., 2016; Colombo & Grilli, 2005; Holbrook, Cohen, Hounshell, & Klepper, 2000; Roberts et al., 2011). Consequently, it is relevant to examine how the founding team size interacts with the prior industry experience of the founding team.[1]

Empirically, examining the startup hiring process is fraught with several difficulties. Hiring requires an agreement, that is, a match between the founding team and a new hire. Failing to recognize the mutual aspect of the matching and the interdependence between each side's

[1]Consistent with prior work (Agarwal et al., 2016; Delmar & Shane, 2006), we perceive the size of founding teams as a broad proxy for resources, market opportunities and intellectual property that founders bring to their startups. To calculate the founding team size, we use employment data and thus include all individuals who were involved in a startup at an early stage (Agarwal et al., 2016; Balasubramanian & Sakakibara, 2015).

selection leads to erroneous statistical inferences (Mindruta, Moeen, & Agarwal, 2016; Pan, 2015; Park, 2013).[2] Further, unobserved factors may drive both the selection into a startup and employee earnings. We implement a novel two-sided assortative matching model supplemented by an outcome equation (Chen, 2013; Ni & Srinivasan, 2015; Park, 2013; Sørensen, 2007) and show how traditional regressions fall short in estimating this phenomenon. The two-sided matching models are highly relevant in this context, because the selection is mutual and each side's quality differences matter in the hiring.

We study these questions in the context of five technology manufacturing industries in which prior industry experience plays an important role such as computers and electronic product manufacturing, and transportation equipment manufacturing (Agarwal et al., 2004; Holbrook et al., 2000; Klepper, 2002) using the U.S. Census Bureau employee-employer linked data set (Longitudinal Employer Household Dynamics, LEHD). The estimation produces two sets of results—drivers of a match and drivers of employees' short-term earnings. First, we find that new hires prefer startups whose founding teams have prior industry experience when the founding team size is small. We also find that startups continue to prefer to attract and accumulate employees with prior industry experience beyond the founding stage. These findings imply that the role of prior industry experience is more complex than previously thought. Even founders who lack relevant industry experience may attract new employees with such experience *if* they are able to assemble a large founding team (i.e., are able to assemble resources despite not having industry experience). Second, after selection is conditioned out, we find that the employees' short-term earnings are mainly driven by their earnings from their previous job, while receiving a premium for their prior industry experience.[3] Overall, we show that startups continue to value and accumulate human capital with prior industry experience beyond the founding stage.

Highlighting the usefulness of two-sided matching, we show that traditional estimation methods do not reach these conclusions. For instance, discrete choice models show that startups prefer employees without prior industry experience. This is at odds with studies documenting that entrepreneurs with industry experience perform better (Agarwal et al., 2004). The traditional regressions provide problematic estimates in our context because they overlook the interdependence of choices (i.e., if an employee has been hired, she is not available for the next startup). Further, traditional regressions rely on the variation in the number of matches for identification. However, individuals with more matches may be unobservably different than those with fewer matches. A two-sided matching model helps to address both problems. The results also reveal significant differences between matching and traditional OLS regressions when estimating earnings. Differences attributable to individual marginal effects between the two models lead to swings often exceeding 5% of the total predicted earnings. Further, while the OLS regressions indicate that employees' earnings depend on the startups' characteristics that influenced the match, the matching estimates reveal the employees' prior earnings as the main driver of their current earnings. Specifically, the regression results show that founding team size drives employees' earnings, while matching shows it only affecting the likelihood of a match but not earnings. Using regressions thus leads us to erroneously conclude that short-term

[2]We use the term "selection" to represent agents "selecting" each other. However, scholars using assortative matching models often use "sorting" instead as a label for the labor market mechanism. We use both terms interchangeably.
[3]Note that our findings do not imply that the short-term earnings of new hires are higher in startups than in established firms—only the portion attributable to industry experience. While the short-term earnings typically decline posttransition to startups (Campbell, 2013), the compensation may eventually become higher (Zenger, 1994) or lower (Hamilton, 2000).

earnings of startup employees vary with resources brought in by the founding team (as proxied by the founding team size), which may not be the case.

The innovative approach this study brings to these questions allows us to contribute to multiple streams of literature. The study contributes to the literature on the role of prior experience in entrepreneurship. While prior industry experience of founders contributes to average startup performance (Agarwal et al., 2004; Chatterji, 2009; Colombo & Grilli, 2005), its role may not be as simple as prior research implies. Even startups that do not inherit industry experience through their founders may attract employees with such experience under some conditions. More broadly, we contribute to the literature on entrepreneurial human capital (Campbell, Coff, & Kryscynski, 2012; Coff, 1997) by modeling the matching between startups and new hires while highlighting the human capital characteristics that are important in this process. Our study shows that prior earnings play a relatively less critical role compared to other predictors of future performance when individuals *select* startups. However, individuals working for startups still receive an earnings premium for their industry experience relative to their earnings at established firms. This paper is possibly the first to apply a two-sided matching model supplemented by an outcome equation in the context of entrepreneurship, which complements the work on matching models in the strategy literature (Mindruta et al., 2016). The method illustrates handling endogenous matching relationships when instruments are not readily available (Chen, 2013; Ni & Srinivasan, 2015; Park, 2013; Sørensen, 2007).

2 | THE ROLE OF PRIOR INDUSTRY EXPERIENCE IN ENTREPRENEURSHIP

Entrepreneurs often gain industry experience in established firms prior to starting their own businesses in the same industry. Prior research has identified many benefits associated with such *prior industry experience*. First, prior industry experience may help employees identify entrepreneurial opportunities (Bhide, 1994; Sørensen & Fassiotto, 2011). If for various reasons, the established firms do not exploit the opportunities, the employees may exit to do so through their own firms (Cassiman & Ueda, 2006; Gambardella, Ganco, & Honoré, 2015; Thompson & Klepper, 2005). Second, prior industry experience provides individuals with knowledge about the industry. Studies often emphasize technological knowledge that employees gathered and transferred to their own ventures (Agarwal et al., 2004; Klepper & Sleeper, 2005). Prior industry experience can also be a source of relevant marketing (Agarwal et al., 2004), regulatory (Chatterji, 2009) and organizational knowledge (Agarwal et al., 2016), or valuable relational resources such as client ties (Raffiee, 2017). Consistent with these benefits that prior industry experience entails, startups with founders having such experience tend to outperform new ventures whose founding teams lack the experience (Agarwal et al., 2004; Chatterji, 2009; Roberts et al., 2011). Further, prior literature has reported a positive relationship between the prior industry experience of the founding team and the size of either the founding team (Colombo & Grilli, 2005; Cooper et al., 1989; Roberts et al., 2011) or the startup firm (Klepper, 2001). If founders hold relevant industry knowledge and experience, it is a strong predictor of future success. This helps to attract more and better individuals to the early startup, which enhances the likelihood that the startup succeeds.

Extant work has predominantly focused on the role of prior industry experience of the founding team in the startup formation phase with implications for performance. However, human capital resources that continue to be assembled as startups grow may play an equally important role. While the role of prior industry experience of the founding team is relatively well understood, the role that such experience plays in the acquisition of new talent has received significantly less attention. We attempt to close this gap by focusing on the role of the prior industry experience during the next stage of the startup life cycle—hiring new employees.

3 | TWO-SIDED MATCHING IN THE ENTREPRENEURIAL LABOR MARKET

A key conceptual and empirical challenge that needs to be addressed when examining the acquisition of talent by startups is the two-sided nature of the matching between employees and firms—each side making a strategic choice regarding their potential partner. While this problem has not been addressed in the context of entrepreneurial firms, it has received increasing attention when studying established firms and inter-firm partnerships (Chatain & Mindruta, 2017; Mindruta et al., 2016).

When a new employee joins a startup, both the startup (i.e., the decision-maker acting on behalf of the startup such as the founding team) and the employee must agree on the mutual selection before they can carry out their work relationship. Both the employee and the firm care about the characteristics of their potential partner because these attributes affect the value that both parties (i.e., agents) can derive from the relationship. Because of heterogeneity, agents on each side compete to enter a relationship with the partner who has the characteristics that they think will maximize their own value associated with the relationship. The competition among the startups on one side and among the employees on the other side first leads to mobility but eventually ends up in a state in which none of the agents has an incentive to find another partner (Gale & Shapley, 1962; Roth & Sotomayor, 1992). In our entrepreneurial context, employees maximize their value (i.e., utility) associated with working for a startup. Conditional on willing to be hired by a startup, employees will prefer to work for the startup that will maximize this expected value. Many characteristics of the startup may influence the choices made by the employees. Similarly, the startups will prefer to work with employees that can maximize their expected value and, so, compete with other startups to hire employees with specific characteristics.

3.1 | Prior industry experience and the matching between startups and employees

In technology manufacturing industries, prior industry experience is likely to be one of the characteristics that is relevant for hiring because the knowledge that is necessary to perform tasks is more complex than in less technological industries. Specifically, prior industry experience may help founders and employees master new technologies or identify new market opportunities (Gambardella et al., 2015; Helfat & Lieberman, 2002). As we discussed above, prior industry experience may also help transfer opportunities (Klepper, 2001), regulatory knowledge (Chatterji, 2009), and marketing knowledge (Agarwal et al., 2004).

Individuals in the labor market may perceive founding teams in which founders possess prior industry experience as likely to be more successful in the future. Consequently, individuals may perceive such startups as more attractive employment opportunities. Similarly, startups are likely to prefer employees with prior industry experience because workers with such experience tend to perform better in the focal industry (Mithas & Krishnan, 2008; Parent, 2000). Such employees bring industry-specific human capital and, like founders, knowledge about relevant technologies and markets (Gambardella et al., 2015; Ganco, 2013). In summary, founding teams and employees with prior industry experience are likely to be attractive to each other. Existing literature thus implies a positive assortative matching between startups and employees based on prior industry experience.

Prior research also indicates that founding team industry experience positively relates to founding team size and early firm size (Colombo & Grilli, 2005; Cooper, 1985; Roberts et al., 2011). Larger and better founding teams are then also associated with a higher probability of success (Agarwal et al., 2016; Cooper et al., 1989; Holbrook et al., 2000). Since both prior industry experience of the founding team and founding team size represent predictors of future startup performance, new hires may prefer startups that have both. Alternatively, as prior industry experience might first have affected initial size, startups may not have to provide both to attract valuable hires. The founding team size and the founding team prior industry experience may be different proxies of the same unobserved underlying startup quality, such as the ability of the startup founders to recognize and exploit entrepreneurial opportunities. Consequently, it is useful to examine how founding team size and prior industry experience interact in their effect on the hiring of new employees.

3.2 | Prior industry experience and employee earnings conditional on matching

Prior industry experience may not only affect the match between startups and employees, but it might also drive the immediate outcome of the newly formed relationship: the employees' earnings. Conventional wisdom suggests that both founders and early employees will earn on average less than they would in employment at large firms (Evans & Leighton, 1989; Hamilton, 2000). A discussion has emerged on whether such entrepreneurship discounts are contingent on context, and what drives them (Åstebro & Chen, 2014; Levine & Rubinstein, 2017; Zenger, 1994). Both pecuniary and non-pecuniary reasons may explain why employees prefer working for startups in some cases. On the non-pecuniary side, certain individuals prefer the less structured and more malleable nature of an entrepreneurial workplace (Lazear, 2005; Roach & Sauermann, 2015). From the pecuniary perspective, startups can provide closer alignment between performance and individual compensation (Elfenbein, Hamilton, & Zenger, 2010; Zenger, 1994) and offer tradeoffs between short-term and long-term performance relative to large firms (Campbell, 2013). Employees may accept lower short-term compensation in return for the prospect of higher returns in the future.

The question related to our investigation of startup employees' earnings is whether prior industry experience may explain part of the earnings heterogeneity. Startups should not only prefer employees with prior industry experience but may also provide an earnings premium to such employees. This argument is consistent with prior work that industry-specific experience is a relevant driver of earnings premiums in the labor market (Abowd, Kramarz, & Margolis, 1999; Mithas & Krishnan, 2008). Neal (1995) found that displaced workers in the United States who switch industries undergo a larger earnings decline than those who stay in the same industry. Further, he reports that earnings for industry stayers are impacted by industry seniority as much as by job seniority. In a more general study using a U.S. nationwide sample, Parent (2000) found that industry tenure explains a greater portion of hourly income than firm tenure.

While the effect of prior industry experience of an employee on her earnings is likely positive, the effect of prior industry experience of the founding team on earnings is less clear. On one hand, founding teams with prior industry experience may expect higher performance in the future and thus may be able to afford to offer higher earnings to attract higher quality employees. On the other hand, if the prior industry experience of founders foreshadows future growth and success of the startup and, thus, higher future compensation, the employees may be willing to accept lower short-term compensation if they join a startup in which the founders have prior industry experience. Conditional on the positive assortative matching between startups and employees, we thus expect that individuals with prior industry experience will receive an earnings premium.

4 | DATA

One of the difficulties in studying startups' employment is obtaining access to data that systematically track employment history in startups' early stages. To this purpose, we gained access to the Longitudinal Employer Household Dynamics (LEHD) data set from the U.S. Census Bureau, which links employees to employers in the United States for over twenty years. The LEHD is constructed from unemployment insurance records and provides quarterly information on all employees for which employers paid contributions to the state unemployment insurance fund (McKinney & Vilhuber, 2011). The LEHD consists of three files: the Individual Characteristics File with individuals' date of birth, gender, race, education, and citizenship; the Employer Characteristics File with the establishment's industry, payroll, state and county; and the Employment History File that connects establishments to individuals every quarter with the individuals' earnings.

4.1 | Pools of startups and employees

To answer our research questions, we need to identify two distinct pools of agents in the labor market: a pool of startups and a pool of employees. We first identified startups from our initial LEHD extract spanning from the 1990s (varying by state) to 2008 (see Appendix Table S1 for a detailed time coverage of the 18 states used in this study). We restricted our pool of startups to the ones created between 2000 and 2006 (to create the pre-founding measures) that hired at least one employee between 2003 and 2007 (to have a pool of one-, two-, and three-year-old startups each year). Specifically, we selected startups that were older than five quarters and younger than four years (i.e., exist between their 6th and 16th quarters). We focused on the period after the first year (plus one quarter) of the startup's existence because the first year has typically been associated with the formation stage during which founders, cofounders, and early employees form the founding team (Hanks, Watson, Jansen, & Chandler, 1994).[4] Our data do not allow us to identify these different roles. We thus assume that the individuals employed by the startup during its first year compose the founding team that will hire the new employees

[4]We added one quarter to the founding stage to be able to include companies founded in the first quarter while still observing one full year of their existence. The first five quarters include the one-year birthday of all startups.

subsequently. As a robustness check, we ran our model using the team assembled during the first quarter of existence and found similar results (Table S5a,b). These quarter cutoffs provide a reasonable sample size while still covering the firms in their early stages. The last year to which we have access, 2008, is used to measure the earnings of the employees hired in 2007. Further, we narrowed our pool to five technological manufacturing industries, which are at the three-digit NAICS level: Fabricated Metal Product Manufacturing; Machinery Manufacturing; Computer and Electronic Product Manufacturing; Electrical Equipment, Appliance, and Component Manufacturing; and Transportation Equipment Manufacturing (Table S2).[5] We chose these industries because of the importance and heterogeneity of the human capital involved. The occupations range from machinists to mechanical and industrial engineers (Table S3 lists the most common occupations). The size of the markets given by the population of firms and individuals in these industries makes the matching estimation feasible. The sample is comprehensive in its scope and many of the industries examined in the prior work on employee entrepreneurship are included (Holbrook et al., 2000; Klepper, 2002). Based on the U.S. Department of Commerce, these industries represent about 9% of GDP and 4.4% of employment. Our final startup pool is the population of startups meeting the criteria and consists of about 1,000 startups.[6]

To build our pool of employees, we identified all employees hired by the pool of startups. We excluded employees who did not earn, the year before joining the startup, at least the earnings threshold of $52,000, which is the minimum average yearly earnings among the most common managerial jobs in the five industries.[7] There are two reasons for this exclusion. First, because the LEHD is a census of all workers, including part-time workers and workers with multiple jobs, the sample must be trimmed to only include workers for whom matching to a specific job is economically meaningful (Campbell, Ganco, Franco, & Agarwal, 2012). Second, we want to restrict the analysis to individuals who are critical for startup performance and, thus, choose the minimum earnings of a managerial position across the five studied industries. By trimming our group of employees, this approach makes the assortative matching estimation technically feasible by limiting the number of individuals at risk of matching. Our pool of employees is made of around 4,000 individuals.

For the matching estimation, the pools of startups and employees are organized into markets where agents pair up with each other. A market is configured as a state-industry-year entity, which should be a reasonable configuration because individuals who change jobs, while being employed at a supervisor-level position the year before are expected to know the industry and state in which they want to work (as a robustness check, we ran the model with a state-year market structure, showing consistent results).[8] Structured this way, the data set is made up of 110,000 dyads, which represent all the potential combinations between a startup and an employee in a given market. By comparison, without a market structure, the total number of dyads would be $1{,}000 \times 4{,}000 = 4{,}000{,}000$. This would not make economic sense as the employees are not permanently on the job market for five years across all states and all industries. This state-industry-year structure leads to around 120 markets that, on average, consist of around 900 dyads of 60 employees and around 15 startups. These numbers make it reasonable

[5]Our results are not specific to any of these individual industries.

[6]The numbers of observations are rounded per disclosure requirements of the U.S. Census Bureau.

[7]The minimum average yearly earnings of the most common managerial jobs in the five industries is based on the public data of the Bureau of Labor Statistics. http://www.bls.gov/iag/tgs/iag335.htm#earnings (in 2008 dollars).

[8]These individuals can still be employed in any state or industry available in the LEHD before joining the focal startup.

for both startups and individuals to be aware of each other's characteristics within the market and for all potential pairs in a market to serve as counterfactuals.

4.2 | Dependent variables

The matching outcome, $M_{ij} = 1$, occurs when the startup i pairs up with the employee j. Every employee is matched exactly once, while every startup is matched at least once. In the outcome equation, we followed prior research (Braguinsky, Klepper, & Ohyama, 2012; Parent, 2000) and used the natural logarithm of the annual earnings of the employee in the first year since they joined the startup. The earnings provided by the LEHD include wages, bonuses, and exercised stock options obtained during their employment at the startup. Given that employees only worked for a year at the time of the measurement, wages are likely to make up most of the earnings.

4.3 | Independent variables

The founding team variables and employee variables are conceptually the same, but they are measured at different times and across different individuals. For instance, a startup created in the first quarter of 2003 has its founding team variables measured from the beginning of the LEHD up to 2002. If the startup hires an employee in the second quarter of 2004 (i.e., during its 6th quarter), 2004 is the year t during which the employee is hired. The variables capturing her experience are measured from her first appearance in the LEHD, most likely in the 1990's up to 2003 (year t-1 for the employee) while her startup earnings are measured in 2005 (in year $t + 1$ for the employee).

Prior industry experience relates to the industry knowledge that an individual acquires through work experience in the industry of the startup and is measured as the number of years an employee worked in the 3-digit NAICS industry of the startup before being hired in the startup. We then break down the variable into three dummy variables to be able to detect any nonlinear relationship between experience and matching (e.g., technological knowledge may have a short lifecycle and the marginal value of very long industry experience may be low). We choose the cutoffs for the dummies to balance the number of observations represented by each dummy. The three employee dummies ("Employee's ind. exp." in tables) are: no prior industry experience; more than zero but less than or equal to five years; and strictly more than five years. The omitted category is the no prior industry experience category. The tails of the employee's experience distribution are heavier, while the tails of the founding team's experience distribution are lighter.[9] Hence, we use the following three dummies for the founding team ("Founding team's avg. ind. exp." in tables): no prior industry experience; more than zero but less than or equal to three years; and strictly more than three years.

Founding team size is the number of individuals having an employment relationship with the startup at the time of its 5th quarter of existence. Following prior work using the LEHD, we attribute the status of founders to these first employees if they had earned at least an average of $10,000 yearly over their career, which shows an attachment to the labor market (Campbell, Ganco, et al., 2012). On average, our teams are made up of 7.8 team members. This mean is

[9]The number of observations per dummy cannot be disclosed due to U.S. Census confidentiality rules.

higher than means reported in several prior studies where they range between 1.5 and 3.5 (Colombo & Grilli, 2005; Cooper et al., 1989; Ruef, Aldrich, & Carter, 2003).[10] Three reasons explain our higher mean. First, our data only includes incorporated businesses that were started by at least two people, while prior work often includes teams of size one and self-employed individuals. If we include startups founded by one individual, our average team size drops to 4.36. Second, manufacturing industries require larger teams than other industries such as services, retail, or construction.[11] Third, our approach counts very early joiners of a startup as members of the founding team even if these individuals were not present when the business was incorporated. While prior studies vary on who they count as members of the founding team, we are consistent with studies relying on employment data (Agarwal et al., 2016; Balasubramanian & Sakakibara, 2015).

As controls, we include the *prior earnings* variable to proxy for general ability (this control can be alternatively seen as a reservation wage) 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., 2016; Braguinsky et al., 2012). We measure *college degree*, which is coded one if the worker has reached at least 16 years of education (six years of elementary school, six years of high school, and four years of college) and zero otherwise. *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—that is, was employed the first year the startup was created (Shane & Stuart, 2002). *Age* is a proxy for the time an individual acquired general experience (Jovanovic, 1979). Because the relationship between age and matching is again unlikely to be linear, we break the age variable down into four dummies: less than 30 years; more than 30 but less than 40 years; more than 40 but less than 50 years; and more than 50 years. We also include demographic controls. *Male* is coded 1 if the worker is a male and 0 otherwise. *White* is coded 1 if the worker is white and 0 otherwise. *Non-US citizen* is coded 1 if the worker is not a U.S. citizen and 0 otherwise. The founding team variables are the averages of the founding team members' variables. In addition, we control for the labor market conditions in which the startups and employees reside with *the number of new establishments in the county* of the startups during the focal year and *the labor market-active population in the county*, which is the number of active workers in the employee's county the year before joining the startup. Finally, the earnings equation includes year, industry, and region dummies.

5 | ESTIMATION METHOD

Our estimation model captures the mutual aspect of the employment decision, the competition for partners that each agent faces and the interdependence of these choices. Further, we need a model that addresses the endogeneity that could arise due to unobserved factors that affect the selection and earnings. We utilize a two-sided matching model supplemented by an outcome equation (Chen, 2013; Park, 2013; Sørensen, 2007). Figure 1 in the Appendix summarizes the

[10]However, there are specific industries where the average founding team size can be much larger. For instance, the mean number of bank founders is 9.36 in Zheng, Devaughn, and Zellmer-Bruhn (2016) with a minimum of three founders.

[11]Based on the U.S. Census Bureau data, in the manufacturing sector in 2005, the average size in the category of firms of age 0 to 3 years and size between 1 and 49 was 7.1 employees (note that the range includes firms of size one). This number is higher than the services sector with 5.3 employees and the finance, insurance, and real estate sector with 4.1 employees or even the construction sector with 5.1 employees.

assumptions of our model versus those in traditional regressions. Two-sided matching models were originally developed to determine assignment based on mutual selection between two distinct groups: universities and students during college admission (Gale & Shapley, 1962; Roth & Sotomayor, 1992). Recently, these models have become more popular in strategic management in a study of matching between university scientists and firms (Mindruta, 2013), biotech and pharmaceutical firms (Mindruta et al., 2016), and clients and firms (Chatain & Mindruta, 2017).

Two-sided matching models incorporate three key features that make them better tools for understanding hiring by startups than discrete choice models: the voluntary mutual selection between two groups of partners, the competition for better partners and the interdependence of the choices (Mindruta et al., 2016; Pan, 2015; Park, 2013).

5.1 | Assumptions and features

The two-sided matching model and its implementation used in this article are based on Chen (2013). The model has several underlying assumptions. Two *distinct* sides match—startups and employees. Each employee can only be hired by one startup in each market while startups can only hire up to a given quota of employees. This constitutes the *one-to-many* matching model. The quota exists because startups have limited resources and one startup would not hire all employees even if it is the most attractive employer to these employees. In practice, the quota is the observed number of employees hired in a year by a given startup (each startup uses up its quota). The two sides pair up in a defined market (state-industry-year). In each market, each group has *complete information* on the existence and characteristics of each entity in the other group. The agents know what their options are. In our context of technology manufacturing industries, this assumption appears plausible as each market is made up of a relatively small number of startups and employees.[12]

All agents (i.e., startups and employees) have the same perception of what determines the most attractive counterpart. The focus of the estimation is thus on a general productive value—for example, as driven by qualifications and experience—rather than on the estimation of a match-specific fit.[13] All startups and employees want to maximize the same type of value for which a "best" counterpart exists. Some agents have characteristics that, regardless of the circumstances, will offer a higher value than agents lacking these characteristics will. The matching does not incorporate *unobserved transfers* of utility that agents might set up to obtain a better partner (Chen, 2013).

5.2 | Agents and matching

Let I_t and J_t denote the finite and disjoint sets of startups and employees in market t, where $t = 1, 2, \ldots T$. A market is an industry-state-year entity. The model consists of four equations:

$$M_{ij} = I(\text{startup}\, i\, \text{hires employee}\, j) \tag{1}$$

[12]This informational assumption may not be reasonable in other settings—for example, the food services industry where individuals can easily enter and exit and where many new firms may be hiring.

[13]This corresponds to one of the differences between the Sørensen(2007) versus the Fox (2008) estimators. The Sørensen (2007) estimator is more appropriate for our research question, because we want to examine the *importance* of prior industry experience in startup hiring rather than to examine what drives the *fit* between founding teams and employees.

$$R^s{}_i = S_i\beta + n_i \tag{2}$$

$$R^j{}_j = E_j\gamma + d_j \tag{3}$$

$$Ln(\text{earnings})_{ij} = \alpha_0 + S_i\alpha_1 + E_j\alpha_2 + C_{ij}\alpha_3 + e_{ij} \tag{4}$$

where $M_{ij} = 1$ when the startup i pairs up with the employee j based on the equilibrium obtained from $R^s{}_i$ and $R^j{}_j$, the respective startup and employee latent rankings. S represents the vector of the startup and founding team characteristics; E represents the vector of the employee characteristics; *Ln(earnings)* represents the employee's earnings the year following the hiring year and C represents the vector of controls. The error terms, n_i, d_j, and e_{ij}, are normally distributed.

5.3 | Equilibrium

The underlying value (or utility) that each agent obtains from a match is based on the latent ranking of the partner: the higher the latent ranking, the higher the value. Thus, employees and startups always prefer a partner with the highest latent ranking. A stable equilibrium is reached if there is no blocking pair, so no partner has an incentive to deviate. In other words, the equilibrium is stable if each startup matches with the highest-ranked employee among the set of employees willing to match with the startup and each employee matches with the highest-ranked startup among the set of startups willing to match with the employee. We present the mathematical description of the stable equilibrium based on Chen (2013) in the Appendix.

5.4 | Estimation

We provide an intuitive explanation as to how the model unfolds and can address the endogeneity due to the unobserved characteristics, while providing the mathematical description in the Appendix. The realized matches represent the reached equilibrium. From this equilibrium, the order in the latent rankings can be established, which then will help determine the parameters β and γ, and thus reveal the characteristics that affect the match. The earnings parameters, α, are estimated jointly.

We know that directly regressing the earnings on the startups' and employees' characteristics will likely lead to biased estimation because unobserved characteristics on both sides may affect the mutual selection as well as the earnings. For instance, we may not observe all drivers of the employee's prior success, but the startup might consider some of this information when hiring the employee and determining her earnings. By observing realized matches and outcomes in each market, we can capture the relationship between the unobserved characteristics of the agents and their effect in the earnings equation. Consider a startup with a founding team's industry experience of three years that hires an employee with five years of industry experience and pays her $60,000 a year. In the next market, similar agents match up and the employee is paid $150,000 a year. Given the notable difference, we know that other factors unobserved by us affect the earnings. Going through multiple markets, we can identify the relationships between these unobserved characteristics and the matching parameters and correct the parameters of interest accordingly (Sørensen, 2007; Chen, 2013; also in the Appendix).

Rather than finding exogenous instruments, the matching model relies on the latent ranking as a source of exogenous variation that affects the selection between the employees and startups but not earnings across markets. The implicit assumption is that the distribution of agents across markets is exogenous (Sørensen, 2007).

6 | RESULTS

Table 1 reports the descriptive statistics for our sample of 1,000 startups and 4,000 employees and the correlation matrix for the matched pairs ($n = 4{,}000$). Even descriptively, the founding teams' and employees' prior industry experience are positively correlated. As is common in matching studies (Chen, 2013; Ni & Srinivasan, 2015), we run two OLS regressions using the matched pairs as the first diagnostic step (unreported). In the first one, we regress the founding team prior industry experience on the employees' characteristics, including employee's industry experience. In the second one, we regress the employee's prior industry experience on the startup characteristics, including founding team experience. The founding teams' and employees' prior industry experience are strongly positively related in both regressions. This analysis indicates that prior industry experience is a plausible driver of the matching.

Table 2 presents the results obtained from the matching equation of our three main models. In model 1, we exclude the founding team size, and, on the startup side of the match, we find that employees prefer to join startups whose founding team has up to 3 years of industry experience ($\beta = 0.180$, p-value $= .013$). Regarding the controls, we observe that employees prefer startups with founders who are less than thirty years old, with prior entrepreneurial experience and with some non-US citizens. On the employee side of the match, we find that startups prefer employees with one to five years of prior industry experience ($\gamma = 0.112$, p-value $= .013$). In terms of the controls, startups have a weak preference for males ($\gamma = 0.093$, p-value $= .073$). These results confirm a positive assortative matching between founding teams and employees based on short prior industry experience. In model 2, we add the founding team size, which significantly weakens the effect of the founding team prior industry experience. In model 3, we explore this further by specifying a model with interactions between the founding team size and founding team prior industry experience. We find a strong negative interaction between the founding team size and the founding team prior industry experience, both if less than three years and more than three years, in their effect on attracting new employees ($\beta = -0.023$, p-value $= .099$ and $\beta = -0.030$, p-value $= .048$, respectively). Specifically, founding teams' prior industry experience (<=3 years) is a significant predictor of matching for founding teams that are composed of less than eleven members, while founding teams' prior industry experience (>3 years) is a significant predictor of matching for founding teams that are composed of less than six members. Beyond these thresholds, it is the founding team size that helps to attract new employees.

To interpret the magnitudes of the effect of each variable on the match, we compute its probability advantage, which represents the probability of a given agent being chosen over another agent, everything else being equal (Chen, 2013).[14] The probability advantages are denoted as "P.A." in the tables. For instance, in the interaction model on the startup side of the match, an increase in the founding team size by one *SD* (6.51 team members) provides a probability advantage of 9.78%. A founding team with up to 3 years of prior industry experience has a probability advantage of 14.47% over a team with no industry experience. Teams with up to

[14]The probability advantage is computed as: *{2*[normal cumulative distribution function* $(X_i\beta\text{-}X_{i'}\beta)/2\hat{\ }.5\}\text{-}1\ \forall\ i \neq i'$

TABLE 1 Descriptive statistics for the startups and employees and correlation matrix for matched pairs

Variable			Mean	*SD*	Founding team 1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
Founding team	1.	Founding team size	7.83	6.51	1.00									
	2.	Founding team's avg. ind. Exp.	1.84	2.27	0.02	1.00								
	3.	Founding team's avg. age	39.48	6.56	0.01	0.22	1.00							
	4.	Founding team's entrepreneurial exp.	0.49	0.55	−0.02	−0.01	0.06	1.00						
	5.	Founding team's prior earnings (log)	10.67	0.73	0.07	0.20	0.19	−0.02	1.00					
	6.	Founding team's share of males	0.80	0.21	−0.11	0.09	0.01	0.10	0.10	1.00				
	7.	Founding team's share of whites	0.66	0.32	−0.06	−0.07	0.09	0.13	−0.07	0.18	1.00			
	8.	Founding team's share of non-US citizens	0.20	0.26	0.07	0.12	−0.12	−0.09	0.24	−0.13	−0.73	1.00		
	9.	Founding team's share of college educated	0.21	0.2	0.07	0.07	0.18	−0.01	0.39	−0.02	−0.10	0.18	1.00	
	10.	Number of new establishments in county (log)	8.93	1.83	0.02	0.07	0.04	−0.01	0.26	−0.15	−0.39	0.41	0.25	1.00
Employee	11.	Employee's industry experience	3.06	4.21	0.00	0.41	0.06	−0.01	0.08	0.06	−0.02	0.06	0.04	0.07
	12.	Employee's age	41.6	9.52	−0.01	0.03	0.09	0.03	−0.10	0.00	0.01	−0.05	−0.05	−0.03
	13.	Employee's entrepreneurial experience	0.49	0.9	−0.01	−0.03	−0.03	0.12	−0.01	−0.02	0.02	−0.02	−0.02	0.00
	14.	Employee's earnings$_{t-1}$ (log)	11.42	0.49	0.01	0.04	0.02	−0.01	0.33	0.03	−0.13	0.18	0.20	0.19
	15.	Gender	0.87	0.34	−0.02	0.03	0.03	0.01	−0.02	0.12	0.10	−0.06	−0.03	−0.07
	16.	College degree	0.31	0.46	0.01	0.01	0.05	0.00	0.07	−0.02	−0.06	0.06	0.06	0.05
	17.	White	0.69	0.46	−0.04	−0.08	0.01	0.06	−0.18	0.05	0.33	−0.34	−0.15	−0.22
	18.	Non-US citizen	0.22	0.41	0.03	0.09	−0.03	−0.06	0.22	−0.03	−0.28	0.33	0.14	0.23
	19.	Active population in county$_{t-1}$ (log)	11.56	1.58	0.02	0.03	0.05	−0.02	0.24	−0.10	−0.33	0.34	0.24	0.62
	20.	Employee's earnings$_{t+1}$ (log)	11.19	0.83	0.08	0.09	0.05	−0.06	0.40	0.02	−0.11	0.19	0.24	0.24

			Employee									
			11.	12.	13.	14.	15.	16.	17.	18.	19.	20.
Employee	11.	Prior industry exp.	1.00									
	12.	Age	0.13	1.00								
	13.	Entrepreneurial exp.	−0.07	0.00	1.00							
	14.	Employee's earnings$_{t-1}$ (log)	0.06	0.10	0.00	1.00						
	15.	Gender	0.07	0.01	0.02	0.08	1.00					
	16.	College degree	0.03	0.15	−0.02	0.09	0.00	1.00				
	17.	White	−0.03	0.14	0.08	−0.04	0.03	−0.04	1.00			
	18.	Non-US citizen	−0.02	−0.20	−0.04	0.07	−0.01	0.02	−0.55	1.00		
	19.	Active population in county$_{t-1}$ (log)	0.02	−0.02	0.00	0.19	−0.08	0.07	−0.23	0.21	1.00	
	20.	Employee's earnings$_{t+1}$ (log)	0.07	−0.01	0.02	0.44	0.09	0.09	−0.04	0.10	0.21	1.00

Note: if we include startups founded by one individual, our average drops to 4.36.

TABLE 2 Results from matching equation (DV = match between startup and employee, n = 110,000)

Variable	(1) Mean	(1) *p*-value	(1) P.A.	(2) Mean	(2) *p*-value	(2) P.A	(3) Mean	(3) *p*-value	(3) P.A
Founding team's avg. ind. Exp. (>0 & < =3 yrs)	0.180	.013	10.130	0.091	.228	5.103	0.258	.022	14.472
Founding team's avg. ind. Exp. (>3 years)	−0.077	.365	−4.343	−0.056	.521	−3.165	0.168	.206	9.446
Founding team size				0.004	.350	1.579	0.027	.039	9.783
Found. Avg. ind. Exp. (>0 & < =3 yrs) × F. team size							−0.023	.099	−8.543
Found. Avg. ind. Exp. (>3 yrs) × F. team size							−0.030	.048	−11.022
Founding team's avg. age (> = 30 and < 41 yrs)	−0.346	.008	−19.309	−0.435	.001	−24.137	−0.386	.003	−21.486
Founding team's avg. age (> = 41 and < 51 yrs)	−0.183	.188	−10.286	−0.315	.025	−17.601	−0.315	.023	−17.601
Founding team's avg. age (> = 51 yrs)	−0.156	.408	−8.762	−0.257	.182	−14.406	−0.146	.442	−8.224
Founding team's avg. entrepreneurial exp.	0.104	.078	3.221	0.084	.158	2.603	0.073	.217	2.275
Founding team's avg. prior earnings (log)	0.003	.927	0.103	0.024	.391	1.001	0.007	.804	0.297
Founding team's share of males	−0.019	.895	−0.222	−0.057	.695	−0.678	0.114	.423	1.346
Founding team's share of whites	0.040	.772	0.713	0.070	.610	1.271	0.140	.303	2.526
Founding team's share of non-US citizens	0.285	.074	4.181	0.276	.085	4.042	0.232	.142	3.406
Founding team's share of college-educated	−0.100	.515	−1.133	−0.171	.277	−1.934	0.071	.651	0.798
Number of new establishments in county (log)	0.017	.411	1.776	0.010	.627	1.074	0.005	.803	0.547
Employee's ind. Exp.(>0 & < =5 yrs)	0.112	.013	6.291	0.114	.010	6.443	0.086	.054	4.850
Employee's ind. Exp.(>5 yrs)	−0.001	.985	−0.051	0.039	.392	2.223	-2E-4	.997	−0.011
Employee's age (> = 30 and < 41 yrs)	0.019	.772	1.083	0.089	.177	4.991	0.064	.333	3.588
Employee's age (> = 41 and < 51 yrs)	0.050	.465	2.793	0.105	.119	5.914	0.101	.136	5.711
Employee's age (> = 51 yrs)	0.066	.376	3.723	0.147	.046	8.263	0.131	.079	7.370
Employee's earnings$_{t-1}$ (log)	−0.001	.941	−0.033	−0.011	.509	−0.296	0.005	.739	0.149
Employee's entrepreneurial exp.	0.002	.909	0.108	−0.031	.129	−1.442	-3×10^{-4}	.988	−0.014
Male	0.093	.073	5.216	0.063	.225	3.576	0.102	.050	5.722

TABLE 2 (Continued)

Variable	(1) Mean	(1) *p*-value	(1) P.A.	(2) Mean	(2) *p*-value	(2) P.A	(3) Mean	(3) *p*-value	(3) P.A
College degree	0.028	.460	1.602	0.007	.854	0.395	0.009	.809	0.525
White	−0.040	.391	−2.257	−0.039	.395	−2.212	−0.018	.695	−1.021
Non-US citizen	−0.051	.322	−2.894	−0.006	.909	−0.333	−0.027	.604	−1.507
Active population in county$_{t-1}$ (log)	−0.009	.503	−0.811	0.002	.894	0.160	−0.022	.110	−1.926

Note: The mean is computed on the last 18,000 draws; the first 2,000 being discarded for burn-in. The probability advantages (P.A.) are obtained from: {2*[normal cumulative distribution function $(X_i\beta\text{-}X_{i'}\beta)/2$^.5}-1 $\forall$ i $\neq$ i' using a one *SD* increase from the summary statistics for continuous variables. *p*-values are produced by two-sided tests.

3 years of experience see their probability advantage decrease by 8.54% if the team is larger by one *SD*. A founding team with such experience loses its entire probability advantage if the founding team is composed of eleven members or more. On the employee side of the match, the probability advantage of employees with up to 5 years of prior industry experience is 4.85% over employees with no such experience. Further, employees who are fifty-one years or older have a probability advantage over employees of less than thirty years of 7.37% and male employees have a probability advantage over female employees of 5.72%. The probability advantages of these three variables are within a similar range across the models.

Table 3 presents the earnings estimates in which the selection is conditioned out. In the interaction model, the employee's earnings (in the year following her hiring) are positively driven by her earnings from the prior job ($\alpha_2 = 0.47$, p-value = .000). In addition to this strong relationship, employees receive a premium for their prior industry experience. An employee with up to 5 years of industry experience obtains earnings 13.3% higher than an employee without such experience ($\alpha_2 = 0.125$, p-value = .000).[15] As for the employee's prior entrepreneurial experience, we find that an increase in one *SD* (around one prior entrepreneurial experience) increases the earnings by 2.57% ($\alpha_2 = 0.028$, p-value = .014). We also find that a male employee earns 26% more than a female employee ($\alpha_2 = 0.233$, p-value = .000), and white employees earn 16% more than employees of other races ($\alpha_2 = 0.148$, p-value = .000).

The founding team's prior industry experience and the founding team size have no significant effect on the employee's earnings. Still, the founding team's prior earnings positively affect the employee's earnings ($\alpha_1 = 0.17$, p-value = .000). An increase of 10% in the founding team's prior earnings leads to an increase of 1.6% in the employees' earnings. Older founders offer earnings 14% higher on average than less-than-thirty-year-old founders do. Founding teams with entrepreneurial experience offer lower earnings ($\alpha_1 = -0.088$, p-value = .005). If the team had one prior entrepreneurial experience, the earnings are 8.4% lower than if the team had none. If the number of new establishments in the county of a startup increases by 10% the employee's earnings will increase by 0.47% ($\alpha_1 = 0.049$, p-value = .000). An employee's and founding team's prior earnings are the strongest predictors of the employee's earnings in the startup, while the employee's prior industry experience provides an additional wage premium for the employee. In Table 3, we also report the correlations between the error terms of the matching and the outcome, κ and λ (as described in the Appendix in more detail). They have small p-values, implying that unobserved startup and employee characteristics affect the selection and earnings. These unobserved startup and employee characteristics are a source of endogeneity, justifying our estimation approach.

6.1 | Two-sided matching versus traditional regression estimation methods

To illustrate the relevance of using a two-sided matching model, we estimate the results of logit and OLS regressions (Tables 4 and 5). First, we estimate the match. The estimation of one-to-many matching (e.g., full-time employment) requires that every employee is matched with one firm in a focal labor market while a firm can have more than one new employee. When estimating drivers of the match using discrete choice models, the identification relies on the variation in the number of matches that firms and individuals make and assumes that each agent's choice is

[15]Marginal effects for dummy variables are computed as $100 \times (e^{\alpha} - 1)$.

TABLE 3 Results from outcome equation (DV = log earnings$_{t+1}$, n = 4,000)

Variable	(1) Mean	(1) *p*-value	(2) Mean	(2) *p*-value	(3) Mean	(3) *p*-value
Founding team's avg. ind. Exp. (>0 & < =3 yrs)	0.058	.118	0.043	.230	0.002	.973
Founding team's avg. ind. Exp. (>3 years)	0.060	.177	0.016	.702	−0.006	.922
Founding team size			0.006	.002	0.003	.662
Found. Avg. ind. Exp. (>0 & < =3 yrs) x F. team size					0.005	.493
Found. Avg. ind. Exp. (>3 yrs) x F. team size					0.004	.608
Founding team's avg. age (> = 30 and < 41 yrs)	0.152	.041	0.153	.034	0.151	.042
Founding team's avg. age (> = 41 and < 51 yrs)	0.109	.156	0.109	.138	0.121	.114
Founding team's avg. age (> = 51 yrs)	0.108	.290	0.137	.155	0.126	.217
Founding team's avg. entrepreneurial exp.	−0.103	.001	−0.088	.003	−0.088	.005
Founding team's avg. prior earnings (log)	0.176	.000	0.169	.000	0.170	.000
Founding team's share of males	0.029	.692	0.078	.264	0.017	.824
Founding team's share of whites	0.021	.760	0.023	.725	−0.013	.852
Founding team's share of non-US citizens	−0.033	.692	−0.015	.842	−0.034	.688
Founding team's share of college-educated	0.170	.029	0.171	.017	0.122	.119
# of new establishments in county (log)	0.049	.000	0.049	.000	0.049	.000
Employee's ind. Exp.(>0 & < =5 yrs)	0.125	.000	0.123	.000	0.125	.000
Employee's ind. Exp.(>5 yrs)	0.061	.065	0.071	.032	0.067	.041
Employee's age (> = 30 and < 41 yrs)	0.043	.332	0.052	.239	0.053	.239
Employee's age (> = 41 and < 51 yrs)	0.027	.564	0.032	.487	0.039	.401
Employee's age (> = 51 yrs)	0.037	.473	0.038	.455	0.047	.359
Employee's earnings$_{t\text{-}1}$ (log)	0.465	.000	0.468	.000	0.469	.000
Employee's entrepreneurial exp.	0.028	.037	0.025	.072	0.028	.040
Male	0.232	.000	0.218	.000	0.233	.000
College degree	0.061	.021	0.058	.026	0.056	.036
White	0.140	.000	0.143	.000	0.148	.000
Non-US citizen	0.017	.639	0.031	.383	0.025	.490
Active population in county$_{t\text{-}1}$ (log)	0.006	.535	0.009	.386	0.004	.685
Constant	2.582	.000	2.494	.000	2.613	.000
κ	−0.293	.000	−0.206	.027	−0.298	.000
λ	0.279	.000	0.214	.006	0.295	.000
$1/\sigma^2_\nu$	0.443	.000	0.450	.000	0.439	.000

Note: Region, year, and industry dummies are included. *p*-values are produced by two-sided tests except lambda's *p*-value, which is produced by a one-sided test because lambda is assumed to have a truncated distribution to identify the signs of the model.

independent of the other agents' choices. In Table 4, we estimate a set of models using industry-, region-, and year-fixed effects and thus the identification relies on comparing individuals with a different number of hiring events in the focal time period. If we include the market-fixed effects to mirror the data structure of the matching model, the coefficients are not identified because each employee is hired in the focal market once and all the variation is absorbed in the fixed effects. In comparison to the matching estimates reported in Table 2 (Model 2), the logit results reported in Table 4 (Model 2) have higher levels of statistical significance (lower *p*-values) on most of the controls on both sides of the match (top and bottom panels) such as the founding team characteristics and employee characteristics (teams' entrepreneurial experience, share of males, whites, non-US citizen and college education, individual's entrepreneurial experience, race and gender). In logit, the controls may need to do "more work" than in the matching to pick up the quality differences, which are likely correlated with the team and individual demographics. In the matching, the mutual selection based on unobserved quality differences is incorporated explicitly. Further, the differences in the role of prior industry experience on both sides of the match are notable. For instance, in the non-interacted logit model (Table 4 Model 1), the upper panel indicates that new hires prefer founding teams with less focal industry experience (p-value $<.001$), and the lower panel shows that startups prefer employees with less focal industry experience (p-value $<.05$). Such results are inconsistent with prior work on employee entrepreneurship showing that entrepreneurs with focal industry experience perform better than other entrants (Agarwal et al., 2004).[16] However, both signs switch in the matching model to being positive (Table 2 Models 2). Specifically, the effect of employee's industry experience between 0 and 5 years is positive and statistically significant (Table 2), while the effect of founding team's average industry experience between 0 and 3 years becomes positive but not statistically significant (other bins of experience tend to be generally insignificant). In the fully specified model with interactions between team size and the team experience bins, we find, as in the matching model (Table 2 model 3), a positive assortative matching between the first bin of industry experience for each side, startup, and employees. By contrast, in the logit, the founding team's average industry experience between 0 and 3 years and the employee's industry experience between 0 and 5 years continue to be negative. In the logit, the biases are more potent on the individual side, likely because the identification comes from the individuals with multiple matches across markets.

The logit estimates are likely to be biased because they do not consider the interdependence of choices (i.e., taken jobs are not available to other agents), which is what economists define as market sorting. Once we run a logit that is identified (without market dummies), the identification comes from the variation in the number of matches. However, individuals with multiple matches may be unobservably different relative to those with a single match. For instance, individuals with more matches may have longer industry experience but also need to exit the focal market due to their inability to find a match. The matching model generates a variation of conditional probabilities even for individuals with a single match in a focal market and time, and thus provides more robust estimation in a context where unobserved quality differences affect mutual selection.

Second, we estimated the outcome of the match and ran an OLS regression of employees' earnings (one year after the hiring) on the startup and employee characteristics. To compare

[16]As an additional robustness check reported in the Appendix Table S10, we show a positive relationship between startup performance and founding team prior industry experience using OLS (which is consistent with prior work). Consequently, if employees choose rationally, they should be selecting founding teams with more founding team experience, and, intuitively, the relationship between experience and match should not be negative. We thank an anonymous reviewer for suggesting the test.

TABLE 4 Results from logit model predicting startup and employee match (n = 110,000)

Variable	(1) Coeff.	(1) *p*-value	(2) Coeff.	(2) *p*-value
Founding team's avg. ind. Exp. (>0 & < =3 yrs)	−0.203	.000	−0.086	.227
Founding team's avg. ind. Exp. (>3 years)	−0.076	.145	0.087	.261
Founding team size	0.019	.000	0.039	.000
Found. Avg. ind. Exp. (>0 & < =3 yrs) x F. team size			−0.020	.011
Found. Avg. ind. Exp. (>3 yrs) × F. team size			−0.025	.003
Founding team's avg. age (> = 30 and < 41 yrs)	0.038	.690	0.030	.756
Founding team's avg. age (> = 41 and < 51 yrs)	−0.122	.214	−0.135	.170
Founding team's avg. age (> = 51 yrs)	−0.276	.030	−0.282	.027
Founding team's avg. entrepreneurial exp.	0.075	.039	0.076	.037
Founding team's avg. prior earnings (log)	0.309	.000	0.312	.000
Founding team's share of males	0.126	.165	0.129	.155
Founding team's share of whites	0.222	.005	0.208	.009
Founding team's share of non-US citizens	−0.428	.000	−0.440	.000
Founding team's share of college-educated	0.367	.000	0.353	.000
# of new establishments in county (log)	−0.004	.773	−0.001	.928
Employee's ind. Exp.(>0 & < =5 yrs)	−0.104	.017	−0.103	.017
Employee's ind. Exp.(>5 yrs)	−0.052	.241	−0.051	.250
Employee's age (> = 30 and < 41 yrs)	0.077	.224	0.076	.229
Employee's age (> = 41 and < 51 yrs)	0.044	.497	0.044	.504
Employee's age (> = 51 yrs)	0.003	.965	0.003	.962
Employee's earnings$_{t-1}$ (log)	−0.060	.117	−0.060	.117
Employee's entrepreneurial exp.	0.028	.146	0.028	.146
Male	0.048	.340	0.049	.333
College degree	−0.007	.857	−0.007	.860
White	0.076	.089	0.076	.090
Non-US citizen	−0.103	.041	−0.102	.043
Active population in county$_{t-1}$ (log)	−0.027	.033	−0.027	.032
Constant	−6.169	.000	−6.323	0.000

Note: Region, year and industry dummies are included. *p*-values are produced by two-sided tests.

the results between the regression and the matching model, we computed the effect sizes (Coe, 2002). The key feature of the matching outcome estimation is that it allows separating the effects of variables on the match from their effect on the outcomes of the match. In terms of the controls, in Table 3 Model 2 (i.e., non-interacted model), several startup characteristics are predictive of the match. For instance, examining the OLS of the same model (Table 5 Model 1), we observe that the coefficients on the founding team's avg. age is between 30 and 40 years and the founding teams' entrepreneurial experience are 0.79 and 0.47 SDs larger in OLS than the matching model, respectively. Even larger differences appear in the interacted model (Table 3

TABLE 5 OLS regression of employee's logged earnings in $t + 1$ ($n = 4{,}000$)

Variable	(1) Coeff.	(1) p-value	(2) Coeff.	(2) p-value
Founding team's avg. ind. Exp. (>0 & < =3 yrs)	0.046	.154	0.058	.223
Founding team's avg. ind. Exp. (>3 years)	0.003	.937	0.050	.351
Founding team size	0.006	.000	0.011	.034
Found. Avg. ind. Exp. (>0 & < =3 yrs) x F. team size			−0.003	.553
Found. Avg. ind. Exp. (>3 yrs) x F. team size			−0.007	.240
Founding team's avg. age (> = 30 and < 41 yrs)	0.099	.122	0.094	.144
Founding team's avg. age (> = 41 and < 51 yrs)	0.066	.314	0.062	.349
Founding team's avg. age (> = 51 yrs)	0.110	.204	0.109	.209
Founding team's avg. entrepreneurial exp.	−0.075	.004	−0.073	.005
Founding team's avg. prior earnings (log)	0.169	.000	0.168	.000
Founding team's share of males	0.065	.297	0.059	.343
Founding team's share of whites	0.032	.575	0.026	.653
Founding team's share of non-US citizens	0.009	.900	0.002	.977
Founding team's share of college-educated	0.165	.008	0.160	.011
# of new establishments in county (log)	0.050	.000	0.051	.000
Employee's ind. Exp.(>0 & < =5 yrs)	0.104	.000	0.103	.000
Employee's ind. Exp.(>5 yrs)	0.061	.048	0.062	.044
Employee's age (> = 30 and < 41 yrs)	0.043	.300	0.044	.299
Employee's age (> = 41 and < 51 yrs)	0.021	.623	0.021	.636
Employee's age (> = 51 yrs)	0.017	.716	0.017	.715
Employee's earnings$_{t-1}$ (log)	0.470	.000	0.470	.000
Employee's entrepreneurial exp.	0.029	.022	0.029	.025
Male	0.213	.000	0.213	.000
College degree	0.056	.024	0.056	.023
White	0.150	.000	0.151	.000
Non-US citizen	0.033	.323	0.034	.315
Active population in county$_{t-1}$ (log)	0.008	.401	0.008	.413
Constant	2.509	.000	2.505	.000
R-squared	0.322		0.323	

Note: Region, year, and industry dummies are included. *p*-values are produced by two-sided tests.

model 3). The founding team experience, team size and the interactions between these variables are all overestimated in the OLS with an effect size difference between the OLS and the matching outcome of a SD of more. In the matching equation, these variables have large effects on the mutual selection (Table 2 model 3). Thus, it is not surprising that their estimation would be biased in the OLS as their effect on selection is not captured. Indeed, the OLS relies on the assumption that the errors are iid, while the matching considers that errors are correlated between the selection and the outcome equations. The coefficient on the founding team size is the most representative of this issue as it is significant in the OLS but not in the outcome equation. The effect in the OLS estimate is 1.32 SD higher than the analogous effect in the outcome equation, translating into a difference of $5,705. Similarly, founding team age between 30 and 40 years negatively predicts the match (Table 2). Here, the OLS underestimated the effect by 0.82 SD relative to the outcome equation. When the dummy variable is set to 1, it translates into a difference of $4,662 between the two estimation techniques. On the employee's side, the employee's industry experience between 0 and 5 years is the main predictor of the match, and it is underestimated in the OLS by 0.69 SD. When the dummy variable is set to 1, it translates into a difference of $1,788 between the two estimation techniques. When estimating earnings, the OLS tends to overestimate and underestimate the effects of the variables depending on whether they positively or negatively predict the match on the startup or employee's side, translating into large swings in predicted earnings. While the pattern of coefficient signs is qualitatively similar between the OLS and the outcome equation, the differences in the magnitudes of the coefficients are significant. This is because the OLS estimates confound the effects of the variables on earnings (the outcome of the match) and matching (sorting into the match).

6.2 | Robustness checks

We implement a range of robustness checks to stress test our findings and mechanisms. All the results are presented in the Appendix. First, our theoretical motivation and the main models (Tables 2 and 3) are designed to examine the effect of founding team industry experience on the hiring of new employees in the early stage of the startup lifecycle. If indeed the founding team experience is the mechanism behind our results, its effect should weaken as the startup ages. This is because survival serves as a credible indicator of future performance. To examine this, we take advantage of startups that are one, two and three years old and interact their age with prior industry experience. In the Appendix Table S4a model 1, we find that the effect of the founding team industry experience weakens as the startup ages. In model 2, we add the interaction between founding team size and experience and again observe a negative interaction between the startup age and industry experience. The negative interaction between the founding team size and industry experience is qualitatively similar to our main model (Table 2, model 3) albeit statistically weaker. In the outcome equation (Table S4b, model 1), we find results consistent with our main models presented in Table 3. The employee's earnings are mainly determined by the employee's characteristics such as prior earnings, prior industry experience, gender and race.

Second, we would like to examine whether our results are robust to the timeframe we used to measure the founding team characteristics. Instead of using the first-year mark to capture the composition of the founding team, we used the first quarter. The fifth quarter allowed us to include founders who might have needed longer transitions to leave their previous jobs before being formally employed by the startups. The first quarter allows us to isolate the very early team running the startup. In Table S5a, we found results consistent with our main analysis with the same negative interaction effect between founding team size and founding team industry experience. Founding teams' prior industry experience (<=3 years) is a significant predictor of matching for founding teams that are composed of less than seven members. In the first quarter, startups still prefer to hire employees with industry experience. In Table S5b, we also report that the employees' earnings are mainly determined by their own prior earnings, experiences, and demographic characteristics. As before, the founding team's prior earnings also affect the new employees' earnings.

Third, we would like to examine the relative importance of the founding team versus the hires in the previous period on subsequent hiring. New hires may not only match with the founding team but may also match with non-founding employees already at the firm. That is, if a startup enters our data when older than 1 year or if a startup is present multiple years in our data, the hires in one year become the non-founding hires in the next year. We implement two tests to examine this alternative mechanism. In Table S6a,b, we merge the characteristics of the previous non-founding hires with the founding team characteristics. If the non-founding hires play a significant role in the matches, the estimates should change in terms of the effect magnitudes, *SE*s or both relative to our main model. The estimates change very little (Table 2 model 3, Table S6a model 1). For a more systematic investigation of the differences, we compare the effect sizes (Coe, 2002). We find that our variables of interest (team size, experience dummies, and their interactions) are within less than half a *SD* between the two models, suggesting that the additional hires do not alter the effect of founding team size and experience on the subsequent hires. However, we note that the effect of demographics has changed across the two models (with large *p*-values). While speculative, it may indicate that changing demographics, increasing or decreasing diversity, beyond the founding team plays a role in the matches.[17] In the outcome equation (Table S6b), not only do our prior results hold but, in addition, the startup team's size and industry experience now have a positive impact on employees' earnings. Such a finding is not surprising given that hiring is a correlate of growth, which corresponds to higher earnings. Our second test consists of adding the variables computed for the previous hires *separately* into the estimation (Table S7a,b). Our results remain consistent. In addition, startups with many non-founding hires are slightly more attractive to employees. The number of non-founding hires may again indicate future performance ($\alpha_1 = -0.001$, p-value = .080) positively affecting employees' preferences.

Fourth, we wanted to explore the founding team size construct. We conceptualize the founding team size as a proxy indicating future startup success because larger teams have more resources, skills or relationships that will improve their performance. However, one may be interested in isolating the social elements of this construct because, for instance, social proximity between the firm and the employee may drive labor market outcomes separately from the agent characteristics.[18] To examine this issue, we constructed a "home-state" indicator coded as 1 if an employee joins a startup in the state she was born in. The average of the founding team members' home-state indicators is a corresponding variable on the founding team side of the match. Table S8a,b present the results. We find that our estimates of interest remain consistent, while the home state indicator is not a significant predictor of the match. For the earnings, our results remain robust as well. We also found that being hired in their home state has a negative effect on employee earnings ($\alpha_2 = -0.065$, p-value = .022).

Fifth, a challenge in implementing two-sided matching models is in determining the relevant pool of agents that select each other, while respecting the complete information assumption. We test our main models using the industry-state-year structure. To check the robustness, we redefine the matching pools to be much larger by expanding them to state-year.[19] Table S9a,

[17]We leave these results as interesting avenues for future research due to space limitations.

[18]Because we find a significant set of interactions between team size and average industry experience and because the founding team size is not necessarily a significant direct predictor of matching, we are confident that team size is not just a proxy for social proximity between the founding team and the new employee.

[19]It is possible that some of the informational assumptions of the two-sided matching are violated in this setting.

b present the results. The analysis shows results that are consistent with our main analysis. In this configuration, employees prefer founding teams with longer industry experience than before (>3 years). The negative interaction between the founding team size and the founding team experience is preserved and occurs for founding teams with three years or more of industry experience and more than eight team members. On the other side of the match, startups prefer employees with higher prior earnings. Industry experience is a weaker predictor for cross-industry mobility and startups respond to more general indicators of employees' ability such as prior earnings.

7 | DISCUSSION

Our study aimed to explore the role of prior industry experience in the matching between employees and early-stage startups. We set out to examine whether the founding team's and employees' prior industry experiences affect their mutual selection and the employees' earnings to shed more light on how startups accumulate valuable human capital. While doing so, we identify founding team size as an important contingency and indicator of future startup performance. We find that new hires prefer startups in which founding teams had prior experience in the same industry when the founding team size is smaller. Consequently, the role of prior industry experience may be more complex than previously thought. Existing research argues that prior industry experience allows founders to assemble larger founding teams and founding teams with more relevant experience. Our matching model indicates that prior industry experience of the founding team may not be a necessary condition for the ability of the startup to attract employees with relevant industry experience. On the employee side, we show that prior industry experience is not only a valued feature of a founding team, but startups continue to accumulate employees with such experience as they grow. This finding indicates that startups value knowledge and skills that are associated with industry experience not only at the founding stage but also as they grow.

After the selection is conditioned out, we examined how new employees are compensated. We found that employees' earnings are mainly driven by their earnings from their previous job while employees receive a premium at the startup for their prior industry experience relative to earnings in their prior employment. Since the earnings in the prior job should proxy for the general ability of the employee as well as her opportunity costs (i.e., reservation wage), the fact that the startup employment is associated with higher earnings attributable to the prior industry experience may imply that growing startups value prior industry experience more than an average employer in the labor market. While further research is needed to carefully compare the earnings between employment in established and startup firms, our results suggest important implications. If startups value industry experience more than established firms, accumulation of industry-specific skills—for example, due to cross-industry barriers (Starr, Ganco, & Campbell, 2018)—should be associated with an increased likelihood of mobility to startups. From the perspective of the startups, this means that it may be easier to attract individuals away from employment in established firms in the contexts in which the cross-industry mobility barriers facilitate the accumulation of within-industry experience.

In terms of the matching as driven by the demographic control variables, we find that being a male is the characteristic that features most prominently in both the selection and wage determination. Startups prefer to hire male employees over female employees. Furthermore, being male positively affects current earnings despite controlling for prior earnings and education.

The results thus show that hiring and earnings disparities based on gender are also present in the context of technology manufacturing startups and fuel the debate on whether startups are a favorable workplace for women (Khazan, 2015). However, our available data do not allow us to pinpoint the origin of the differences because we do not observe occupations, the nature of their employment contracts (i.e., part-time versus full-time) or human resources practices (Baron, Hannan, Hsu, & Koçak, 2007). Further, we find that being white is associated with an earnings premium, which is consistent with race disparities (Altonji & Blank, 1999). However, as with gender, our data do not allow teasing apart the drivers and we leave such inquiry for future work.

Our study also shows the benefits of applying a novel estimation method in the context of startup hiring. Prior research in entrepreneurship and strategy typically explains phenomena by focusing on the decision of one of the actors. We contribute to the emerging research that models choices as resulting from mutual selection (Mindruta, 2013; Mindruta et al., 2016). Modeling the mutual selection explicitly provides a more robust estimation that reduces biases due to unobserved heterogeneity and potentially provides novel insights. In a traditional approach utilizing a discrete choice model, the interdependence of mutual choices of agents on each side is neglected and such estimation relies on the variation in the number of matches. Matching models are more powerful because they rely on the comparison between individuals with the same number of matches in the focal market but who vary in terms of the latent quality.

We also expand the use of matching models to jointly explain mutual selection and the resulting outcome (Chen, 2013; Park, 2013; Sørensen, 2007). While prior research studied entrepreneurs' earnings (Braguinsky et al., 2012; Campbell, 2013), little is known about the characteristics that influence the earnings of workers joining startups. The matching model implemented in this article allows estimating the drivers of earnings after the selection and sorting are conditioned out. Without considering the role of selection in the earnings determination, one may erroneously conclude that some variables drive earnings, while they only drive selection but not earnings (e.g., founding team size).

More broadly, to evaluate the use of matching models in the context of startup hiring, we provide a detailed comparison between the traditional estimation of startup hiring using OLS and logit models and the matching estimation. Our approach illustrates the costs and benefits of using matching models in an entrepreneurial context. One the one hand, the matching models are significantly more complex to implement, and they necessitate additional assumptions relative to OLS/logit such as the need to carefully define the labor market. On the other hand, matching models may lead to more precise estimates with lower biases. This is particularly important when estimating the outcomes of mutual selection. Matching models thus represent an important complement to traditional estimation methods, and we hope that our study will stimulate more scholars to adopt this approach.

7.1 | Limitations and future research

The strength of the matching model is in presenting results that explain hiring as a two-sided selection (Mindruta et al., 2016). However, its assumptions might create limitations. We assumed that the agents know their preferences in terms of employment and know their possible choices for partners and incur no search cost. This seems reasonable because of our focus on a specific segment of the labor market (i.e., on average, sixty employees and fifteen startups per market). Further, we probed the implicit assumption of the model that startups and employees pay attention to the key variables of interest such as founders' industry experience and founding team size by gathering qualitative evidence from multiple sources such as popular press, a variety of online sources and personal conversations with founders. For instance, one of our informants (serial entrepreneur) mentioned that the industry experience of applicants is a strong predictor of performance, and he uses it as a filter when narrowing down applications. Similarly, another founder who is a recent university graduate mentioned that finding industry experts was a primary objective when hiring early employees. Further, Serbinsky (2019) reports that, based on a conversation with four founders in the auto industry, it is critical to hire individuals with industry expertise. Similarly, Bloomfield (2016), who is a serial entrepreneur, argues that when employees decide on joining a startup, the size and stage of the company are often more important than the industry or the idea itself. Nevertheless, future research may address what drives the attention on each side of the match.

Second, the technology manufacturing industries that we study are located across many states and such distribution is relatively stable over our time frame (see Table S1). This geographic distribution helps us alleviate the risks that startups and employees are all clustered or are drawn to the same location (e.g., Silicon Valley). Clustering would limit the ability of the model to use the exogenous variation of unobserved characteristics across markets and may threaten the assumption of the exogenous distribution of agents across markets. Future research could investigate how assortative matching models could be used for labor clusters.

Third, our estimation of earnings does not include unrealized stock options and equity awards because we lack such data. Our results may be conservative as stock options and equity awards are likely to increase the earnings premium in startups associated with industry experience. To the extent that the observed compensation (earnings) proxy for the unobserved compensation (stock), the earnings estimation should lead to the lower bound estimates.

Fourth, the U.S. Census' LEHD coverage improves the validity of the results in the context of our technological manufacturing industries but comes with the trade-off of missing fine-grained information. Future research can extend this study to other industries where other types of experiences or skills might play a larger or lesser role than industry experience (Starr et al., 2018). Because of data coverage as well as the computational burden associated with matching, we limited our analysis to the very first years of the startup's lifecycle. Future research can investigate later stages when human resource management may be more professionalized (Baron et al., 2007). Further, these avenues could combine a focus on gender differences, which would enhance our understanding of the sources of gender disparities in startups.

8 | CONCLUSIONS

Using a two-sided matching model supplemented by an outcome equation, we investigate the effects of prior industry experience on hiring by startups and on the new employees' subsequent earnings in five U.S. technological manufacturing industries. The results show that the role of prior industry experience is more complex than previously thought. While startups select employees with relevant industry experience, employees select startups based on prior industry experience when the founding team size is small. Further, we find that the new employee's earnings are determined by their prior earnings, prior industry experience, and demographic characteristics such as gender and race. In general, the study refines our understanding of human capital accumulation and compensation in startups with implications for the literature on employee entrepreneurship and strategic human capital. It also opens new avenues for future work using a two-sided matching approach in the entrepreneurial context.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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