Spring 2022

Human Capital in Innovation-Driven Environments

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Abstract

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Organization leaders and policymakers express the need for developing entrepreneurial and innovative talent, central to firm growth and job creation. Despite the growing number of individuals working at the forefront of innovation and technology, there is much to learn about the role of entrepreneurial and innovative human capital in shaping key organizational processes and outcomes. In my dissertation, I explore how individuals in innovation-driven contexts—such as entrepreneurs, innovators, and investors—vary in their human capital, and how the accumulation of this capital (e.g., knowledge, career experience, expertise), in turn, affects organization performance and innovation.

In the first essay, I explore how the performance of external hires and their teams are affected by mobility and how team design affects the innovation performance of both groups. To do so, I analyze over 63,000 mobility events of U.S. engineers and scientists across different industries. In the second essay, coauthored with Tristan Botelho, we examine the mobility of entrepreneurs to wage employment at established firms. A field experiment was conducted to understand how hiring firms evaluate entrepreneurs as job candidates. In the third essay, I investigate whether allowing the general public, without investment expertise, to invest in startups can provide funding opportunities to a more diverse group of entrepreneurs. Leveraging novel data on startups that participated in Regulation Crowdfunding in the U.S. and data on startups that could have decided to crowdfund, I examine the differences in firm and

founding team characteristics of startups funded by crowd and professional investors.

This dissertation draws on and contributes to research at the nexus of entrepreneurship and organizations. Specifically, the first two essays build on interorganizational career mobility and human capital research. The second and third essays contribute to research on entrepreneurship, evaluation, and resource mobilization. My dissertation offers insights to innovators and entrepreneurs on how to successfully navigate the capital and labor markets. For managers of organizations, the first and second essays highlight ways to develop entrepreneurial and innovative environments. The second and third essays have implications for policymakers on designing entrepreneurship education and funding programs.

Human Capital in Innovation-driven Environments

A Dissertation
Presented to the Faculty of the Graduate School
Of
Yale University
In Candidacy for the Degree of
Doctor of Philosophy

By
Melody H. Chang

Dissertation Directors: Professor Tristan Botelho and Professor Olav Sorenson

May 2022

Acknowledgments

It has been a privilege to study topics fulfilling my curiosity and passion. My dissertation would never have reached its current level of intellectual rigor without the advice of my advisors. I would not have been able to land my dream job without their support and trust.

Since the ideation stage, my advisor Olav Sorenson has always steered me in the right direction, while helping me to think independently and critically. I am constantly inspired by Olav not only for his intellectual strength and commitment to excellence but also for his generosity and care for students. Walking into our meetings with seemingly unsolvable puzzles, I always feel empowered and motivated walking out. My advisor Tristan Botelho has also provided invaluable advice and mentorship. I learned so much from Tristan while working with him on the most fun and rewarding project. Tristan's advice has been very reassuring and bolstered my confidence during challenging and uncertain times. He was always there for me to help me succeed. I will forever be grateful to Olav and Tristan for their warm support and guidance.

I am extremely grateful to my dissertation committee members, Marissa King and Balazs Kovacs. Marissa has provided wise guidance and insightful feedback pushing me to think more deeply about problems. Balazs has been very generous in helping me navigate my academic career. He was the first to guide me through the article writing process and instilled positive energy and optimism. I would also like to thank Amanda Sharkey for offering constructive feedback and warm encouragement since the early days of my Ph.D. years.

Conversations with remarkable scholars and mentors at Yale influenced my thinking and helped me shape my dissertation. I am grateful to Jim Baron, Rodrigo Canales, Julia DiBenigno, Cydnee Dupree, Oriane Georgeac, Ivana Katic, Michael Kraus, Amandine Ody-Brasier, and Amy Wrzesniewski for the opportunity to learn from them. I would also like to thank my wonderful friends and colleagues at Yale for creating a supportive learning environment and making this journey more enjoyable. Especially, Geoffrey Borchardt, Yuna Cho, Dennis Jacobsen, Margeum Kim, Doris Kwon, Jun Won Park, Shuang Song, Elisabeth Yang, and Victoria Zhang have offered feedback on multiple versions of my dissertation chapters and cheered me up along the way. I would also like to express my appreciation for the staff at the Yale SOM Lab, the Initiative on Leadership and Organization, the Marx Science and Social Science Library, and the Kauffman Foundation for providing me with resources to arrive at a more extensive data collection.

My family has given me the strength and courage throughout my doctoral studies. I would not be the person I am today without my parents and their unconditional love, support, and guidance. Both served as my role models and encouraged me to continue learning, pursue my dreams, and believe in myself. Thank you always for being my number one supporters. I feel grateful to have a lovely sister, Haley, my life-long best friend. She has inspired me to become a better person. I also want to thank the Ko family who has brought much more love and happiness to my life. My husband, Charles, was always next to me throughout the peaks and valleys of my studies. He was the first audience for my ideas and presentations. I would not have been able to finish this journey without the support from my loving and caring partner. I dedicate this dissertation to my family.

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Chapter 1

Introduction

Organization leaders and policymakers express the need for developing entrepreneurial and innovative talent, central to firm growth and job creation. A key strategic concern for organizations is to hire, retain, and manage innovative employees. To capture the best and brightest individuals, organizations frequently engage in the competitive war for talent, paying wage premium to recruit human capital from their competitors (Kaplan et al., 2012; Smith, 2018). Organizations are also designing initiatives and programs—such as the creation of innovation centers and labs—to foster entrepreneurial environments and develop their employees to create novel ideas and products within firms (Altringer, 2013). More and more firms are creating positions and departments managing such efforts, not only in the technology sector but also in traditional industries, such as retail and finance. For example, 29 percent of *Fortune 500* firms have a senior innovation executive, a position that was "virtually unheard of [twenty years ago]" (Lovric and Schneider, 2019).

Recognizing the role of entrepreneurial and innovative human capital in organizations and economy, policymakers have also placed a significant focus on nurturing innovators and entrepreneurs. There has been a significant emphasis in including entrepreneurship courses and degrees in colleges and universities (Kauffman Foundation, 2013). Also, government agencies, foundations, and universities have been launching an increasing number of pitch competitions and entrepreneurship support programs to identify and develop individuals with the potentials to bring innovative ideas to fruition.

Despite the growing number of individuals working at the forefront of innovation and technology, there is much to learn about the role of entrepreneurial and innovative human capital in affecting key organizational processes and outcomes. In particular, organizations encounter high levels of uncertainty and information asymmetry when they make important organization decisions—namely, hiring and funding—involving entrepreneurial and innovative human capital.

In terms of hiring, evaluating human capital investment is a key strategic concern for firms. It is difficult to assess capabilities of these individuals and whether the skills and values are transferable when they move to a new organization. In contrast to rising interest among practitioners on how to invest and manage human capital resources, relatively little research has examined whether sourcing innovators externally bring knowledge benefits to the firm, and if so, how they improve firm-level innovation through knowledge sharing with other employees. In addition, while many entrepreneurs enter the labor market after their venture success or failure, it is unclear how hiring firms will perceive and evaluate entrepreneurs as job candidates.

In terms of funding, assessing novel ideas and quality of founders involve high levels of information imperfections. Even professional investors like venture capitalists find difficult to evaluate startup investment opportunities. While existing research on entrepreneurship and resource mobilization has focused on how startup and founder characteristics affect venture outcomes, we have yet to learn how backgrounds and expertise of investors, who make important resource allocation decisions, affect how they evaluate startups and entrepreneurs.

The overarching goal of my dissertation is to better understand how how individuals in innovation-driven contexts—such as entrepreneurs, innovators, and investors—vary in their human capital, and how the accumulation of this capital (e.g., knowledge, career experience, expertise), in turn, affects organization performance and innovation. In particular, I focus on the hiring and funding processes of entrepreneurs and innovators. Specifically, the following research questions guide my investigation:

1. How does the mobility of innovators affect performances of their own and team members? What are the firm-level factors that can maximize innovation performance of both groups?

2. How do hiring firms perceive and evaluate entrepreneurs in the labor market?

3. How does the expertise of investors shape how they assess startups? What are the ways to provide funding opportunities to a broader group of entrepreneurs?

To study these questions, I use multiple methods and data sources. In the first essay of my dissertation (Chapter 2), I explore how the performance of external hires and their teams are affected by mobility and how team design can improve the innovation performance of both groups. I analyze over 63,000 mobility events of U.S. engineers and scientists across different industries.

While the first essay examines the hiring of individuals from established firms, the second essay explores the hiring of entrepreneurs who founded startups. In Chapter 3, coauthored with Tristan Botelho, we conducted a field experiment to understand how founder experience is evaluated by hiring firms, and how the evaluation varies by the outcome of a founder's venture, namely whether their venture succeeded or failed. We submitted applications to 2,400 software engineering positions in six metropolitan areas in the U.S. We test how those who started their career as founders fare relative to those who started their career as wage employees at the initial evaluation stage of the hiring process: receiving a callback for an interview. We also conducted 20 interviews with technical recruiters to provide further insight into our results.

Exploring the role of entrepreneurial and innovative human capital in established firms in the first two essays inspired me to study how the human capital of entrepreneurs and investors influences early-stage venture outcomes. In Chapter 4, I investigate whether allowing the general public, without investment expertise, to invest in startups can provide funding opportunities to more diverse groups of entrepreneurs. Despite growing interest in equity crowdfunding among entrepreneurs and policymakers, it is unclear how crowd investors choose investments and whether their decisions differ from those of professional investors. Leveraging novel data on startups that participated in Regulation Crowdfunding in the U.S. and data on startups that could have decided to crowdfund, I examine the differences in firm and founding team characteristics of startups funded by crowd and professional investors.

This dissertation draws on and contributes to research at the nexus of entrepreneurship and organizations. Specifically, the first two essays build on interorganizational career mobility and human capital research. The second and third essays contribute to research on entrepreneurship, evaluation, and resource mobilization. My dissertation offers insights to innovators and entrepreneurs on how to successfully navigate the capital and labor markets. For managers of organizations, the first and second essays highlight ways to develop entrepreneurial and innovative environments. The second and third essays have implications for policymakers on designing entrepreneurship education and funding programs.

Chapter 2

Cascading Innovation: Performance Implications of Mobility and Team Design

2.1 Introduction

Interfirm mobility by engineers and scientists is an important and common channel for sourcing and transferring knowledge across firms (Almeida and Kogut, 1999; Arrow, 1962; Singh and Agrawal, 2011; Song et al., 2003). In technology-intensive industries, job hopping among patent inventors is prevalent; in the U.S., at least 44 percent of all patent inventors move to another firm at least once, with the average inventor working for 2.5 firms.[1] While the large body of work on mobility and knowledge spillover highlights how an external hire brings a competitive advantage to a firm, research on career mobility and human capital suggests that hiring talent externally also carries significant costs. External hires, who often perform worse after the move,

[1] Calculated by the author based on U.S. patent data from 1975 to 2017. The sample includes movements between U.S. companies and corporations. These figures are most likely underestimates, given that an employee needs to apply for a patent to be included in the sample.

are paid significantly more than incumbent employees (Bidwell, 2011).[2] Organizations incur further costs searching for and then onboarding the best and brightest talent (Glebbeek and Bax, 2004; Shaw et al., 2005). Thus, whether firms realize the targeted knowledge production benefits from new hires is a key strategic concern.

This study therefore explores the following two research questions. First, given the high costs of external hiring, do external hires bring greater performance benefits to their teams? Second, how can firms efficiently organize R&D teams to maximize the innovation performances of external hires as well as other members of their teams? Research on mobility and human capital provides inconsistent answers about how external hires perform following a move. Several studies find a decline in mobile individuals' performance following a move (Campbell et al., 2014; Groysberg and Lee, 2009; Groysberg et al., 2008; Raffiee and Byun, 2019), known as the "portability of performance paradox," while other studies document improvement in post-mobility performance. In addition, we still lack knowledge on how the external hires affect the performance of other employees at the firm. Existing research on knowledge spillover demonstrates that external hires contribute to the firm by introducing knowledge sourced from previous firms (Corredoira and Rosenkopf, 2010; Palomeras and Melero, 2010; Rosenkopf and Almeida, 2003; Song et al., 2003). While these studies have advanced our knowledge regarding the motivation behind external hiring, the process and extent to which an external hire affects the performance of other employees, such as team member productivity or novelty of the inventions, remain enigmatic. Incidentally, Mawdsley and Somaya (2016) have called for more research that both untangles the processes behind learning-by-hiring and investigates successful integration strategies of these hires.

The effective design of R&D teams is an important yet less explored integration strategy in determining the performance of external hires and other members who

[2]Bidwell (2011)'s work examining personnel data from a financial services firm finds that external hires receive 18 percent more compensation than internal promotions.

collaborate with them. The collaborative production of knowledge has been emphasized as a critical source of innovation in technology-intensive industries (Choudhury and Haas, 2018; Singh and Fleming, 2010; Wuchty et al., 2007). This paper addresses how different ways of structuring teams affect the performance of the focal external hires and their team members, as well as how best to assign new hires to teams. Simply adding talent to the mix does not necessarily guarantee successful acquisitions and utilization of human capital (Dokko and Jiang, 2017; Groysberg et al., 2008). The design of R&D teams plays a more important role for external hires because they lack social ties within the new firm, with team boundaries playing a bigger role in determining with whom they will interact and from whom they will absorb new knowledge. Thus, considering R&D team design is important to the broader strategic management of a firm's human capital.

In this paper, I first examine how the mobility of external hires affects the performance of their own and their team members. Drawing on the organizational learning, mobility, and team literatures, I discuss the benefits and costs of working with external hires. Then, I explore how R&D team design influences the innovation performance of external hires and their team members. Specifically, I focus on two firm-level team design factors, "technological experience diversity" (henceforth referred to as "technological diversity" or "knowledge diversity")[3] within team and between team: *within-team diversity* captures whether members of a particular team have similar technological knowledge backgrounds, while *across-team diversity* measures whether teams share more or less diverse sets of technological knowledge with respect to other teams in the firm. While high within-team diversity offers more collaboration benefits than costs to teams, I argue that high across-team diversity can be detrimental to the innovation processes. Further, I investigate the effect of dyadic relations between

[3]There exist many forms of team diversity, including tenure, gender, and functional experience (e.g., Choudhury and Haas, 2018; Hoisl et al., 2017; Pfeffer, 1983; Reagans and Zuckerman, 2001). Here I focus on a dimension that is particularly relevant to an individual's innovation performance.

external hires and other team members—namely, *dyadic knowledge distance*—on the innovation performance of all team constituents.

Using U.S. patent data on a sample of 63,976 mobility events of patent inventors across different industries, I find a noteworthy trade-off between the performance of external hires and their team members. While external hires experience an improvement in innovation performance, the performance of their team members exhibits divergent patterns in terms of the quantity and quality of inventions. Team members (or "teammates"), compared to "non-teammates," experience a reduction in the number of patents after collaborating with the external hire; yet they are more likely to produce inventions with far-reaching technological impact. I also find robust and consistent evidence that a high level of knowledge diversity within a team and a low level of knowledge diversity across teams maximize the innovation performance. Further, assigning new hires to teams with members who have more distant knowledge base can mitigate the negative effect of the productivity decline.

Overall, this study contributes to the literature on mobility and innovation by distinguishing the performance contribution of external hires and the performance ramifications for their teammates. The present paper also has implications for the human capital management literature by assessing whether external hiring is a value creation proposition for the firm. Furthermore, this study contributes to the R&D team literature by proposing effective integration strategies with respect to external hires. The findings have important takeaways for managers at innovation-driven firms. Most importantly, my results suggest that the value of external hiring derives from both the performance of the focal hires and knowledge spillovers to other team members. This performance improvement can be further enhanced by effective team assignment and design. The diverging pattern of teammate performance suggests that firms should carefully consider their immediate performance goals before recruiting efforts.

2.2 Employee Mobility and Innovation Performance

2.2.1 Innovation Performance of External Hires and Team Members

Accessing and acquiring new ideas are central to enhancing the innovation performance of firms (Dokko and Rosenkopf, 2010; Singh and Agrawal, 2011). Through various channels, including acquisitions (Ahuja and Katila, 2001), strategic alliances (Hess and Rothaermel, 2011; Kale and Singh, 2007; Mowery et al., 1996), regional networks (Almeida and Kogut, 1999), and employee mobility (Rao and Drazin, 2002; Singh and Agrawal, 2011; Song et al., 2003), organizations strive to gain external knowledge and ideas to improve technological capabilities. The mobility of engineers and scientists has been the most common channel utilized by firms (Almeida and Kogut, 1999; Rosenkopf and Almeida, 2003; Samila and Sorenson, 2011; Saxenian, 1994).

Despite the strong focus on promoting mobility at the macro level, research on career mobility provides inconsistent findings about whether external hiring is ultimately beneficial or detrimental. Several studies have found that external hires perform worse, at least in the short term, despite firms paying wage premiums to recruit them, an outcome known as the "portability of performance paradox" (e.g., Bidwell, 2011; Dokko and Jiang, 2017; Groysberg et al., 2008; Raffiee and Byun, 2019). These studies examine mobility in various contexts—including the market for investment bankers, security analysts, lobbyists, and NBA basketball players—and offer several reasons for the decline in individual performance after mobility. First, external hires suffer from high adjustment costs due to the limited utilization of firm-specific human capital (Groysberg et al., 2008; Mayer et al., 2012) accumulated from the prior firm. Firm-specific human capital—such as routines, procedures, and interpersonal relationships developed at the prior firm—is not easily transferable and needs to be redeveloped at the new firm. Second, external hires incur high team-level coordination costs working with new colleagues at the hiring firm. Team-specific or colleague-specific human capital could deter external hires from maintaining productivity (Campbell et al., 2014; Ethiraj and Garg, 2012; Jaravel et al., 2018). Every team requires coordination among individuals with specialized knowledge (Rico et al., 2008), and such coordination could be more difficult among members who share fewer similarities in knowledge, routines, and relational capital. For example, Campbell et al. (2014) find that the adverse performance shocks of external hires are reduced when the hires move to a new firm with former colleagues, with established trust and shared routines.

On the flip side, other studies have shown that mobility improves the performance of external hires, thereby improving organizational performance (Hoisl, 2007, 2009; Tartari et al., 2020). These studies argue that when human capital is highly transferable and applicable to a new organization, disruption in firm-specific or team-specific human capital is minimized. For instance, Tartari et al. (2020) show that academic scientists have skills that are less reliant on organization-specific elements; the skills and knowledge for academic research are easily portable and can be utilized after mobility. In addition to minimized costs of mobility in professions with easy portability of human capital, external hires can benefit from knowledge spillovers from colleagues (Hoisl, 2007). Furthermore, scholars have found evidence that mobility improves the match between employer and employee (Topel and Ward, 1992). Employees with poor matches are more likely to move and demonstrate better performance once they have found a better match at the new firm. Hoisl (2009) also finds that high performing inventors are more likely to move and are better able to profit from a move. Even after comparing the performance with control group “non-movers” who have similar observed characteristics, external hires tend to perform better because there could be unobserved factors, like movers being more flexible and ambitious than non-movers.

Although the effect of mobility on external hires has been tested in many other contexts, I revisit the hypothesis in the context of mobility among U.S. engineers and scientists (i.e., patent inventors). Confirming the performance consequences of mobile inventors allows me to then compare the potential costs and benefits associated with hiring with those of other team members, as outlined below. This hypothesis is also an important precondition for subsequent hypotheses, which will examine the organizational design conditions under which external hires can improve performance at the destination firm. While there has been conflicting empirical evidence, I argue that external hires will experience improvement in performance following a move, given that my context is more closely related to studies arguing for performance gains in knowledge production settings (e.g., academics and European patent inventors) characterized by less reliance on firm-specific human capital.

Hypothesis 1: *External hires will experience an improvement in innovation performance when they move to new firms.*

While the performance consequences of external hires has been explored in earlier studies, it is unclear how the performance of teammates who collaborate with external hires are impacted. I discuss both benefits and costs associated with working with external hires on the performance of teammates.

Prior studies in the knowledge spillover literature have examined how firms "learn" by exploiting or accessing knowledge from the recruit's source firm (Corredoira and Rosenkopf, 2010; Palomeras and Melero, 2010; Rosenkopf and Almeida, 2003; Song et al., 2003). This line of research captures learning effects by examining how much destination firms cite the inventions produced by the recruit or the source firm. These studies suggest that firms hire external talent to *exploit* their past inventions. Although past research has improved our understanding of the motivations for external hiring, citing the external hire's prior work does not necessarily mean that firm members have absorbed the new knowledge and improved their innovative capacities.

For example, Singh and Agrawal (2011) find evidence that hiring firms double the use of the recruit's prior inventions and that nearly half of the boost in the use of the recruit's past patents is driven by citations by the recruit and her or his teammates. Although this finding implies that teammates can access the recruit's prior inventions, we still do not know how exactly the new hire contributes to the firm performance through *future collaborative knowledge production*—specifically, whether the teammates can become more productive and produce better quality inventions with greater technological impact after encountering the external hire.

I argue that external hires bring advantages to their teams not only through the exploitation of prior knowledge but also through successful exploration activities, like developing new competencies and recombinations of existing and new ideas (Cohen and Levinthal, 1989). First, teammates working with an external hire are more likely to be exposed to a new, complementary stock of technological knowledge from the external hire's source firm. The large body of work on mobility and knowledge spillover documents how external hires bring new ideas and knowledge from the source firm often not present at the destination firm (Agarwal et al., 2009; Agrawal et al., 2006; Jaffe et al., 1993; Marx et al., 2009; Samila and Sorenson, 2011; Tzabbar et al., 2013). The new knowledge an external hire brings to teammates provides new recipes that, if used with other existing ingredients, can create more combinations of dishes, or outputs. Compared to other existing members at the firm, external hires are more likely to bring in complementary human capital, thereby addressing the knowledge gap in the team or at the firm.

In addition to the influx of new ideas and direct knowledge spillover to teammates, new hires can catalyze team member learning. While incumbent teammates tend to limit themselves to local searches given less motivation to seek, acquire, and absorb information from others (Stuart and Podolny, 1996; Tzabbar, 2009), external hires increase receptivity to new knowledge, thereby sparking exploratory search behaviors by teammates. Moreover, external hires not only bring new knowledge but also social capital, which includes ties to colleagues from the departure firm and additional information networks (Raffiee and Byun, 2019). This expanded network of information and knowledge sources can provide ongoing channels for learning and knowledge spillovers (Reagans and McEvily, 2003; Singh, 2005).

On the other hand, collaborating with external hires may entail additional coordination costs, compared to working with incumbent employees. Although incumbent team members do not incur adjustment costs, they may experience high coordination costs as they assist the external hire with training and onboarding (Rollag et al., 2005). Incumbent teammates also experience coordination difficulties working with external hires who possess distant knowledge with minimal overlapping experience or shared routines (Montoya-Weiss et al., 2001; Weber and Camerer, 2003). However, teammates only need to increase effort for coordinating with one new team member, whereas external hires need to build complementary assets for all members of their new teams.

With the presence of both positive and negative factors that could affect teammate performance, it is difficult to predict, a priori, which effect is stronger. However, given the prevalent notion that an external hire has a positive effect on overall firm-level innovation, I predict that:

Hypothesis 2: *Collaborating with external hires will improve the innovation performance of their immediate collaborators at new firms.*

2.2.2 The Role of R&D Team Design on Innovation Performance

Team Knowledge Diversity

The post-mobility performance of external hires and their teammates is contingent on how the firm organizes R&D teams. Given the increasing dominance of teams in the production of knowledge (Wuchty et al., 2007) and that teams are more likely to produce "breakthroughs" than solo inventors (Singh and Fleming, 2010), it is important to consider how collaborative teams are structured; this determines how employees access, share, and integrate new knowledge (Edmondson and Harvey, 2018; Mortensen and Haas, 2018). Examining the role of team design in the performance of new hires, as well as their teammates, can offer new insights to managers on how to maximize the gains from external hiring.

With its stock of employees who each possesses different knowledge in different technological fields accumulated throughout their careers, managers have discretion in organizing *knowledge diversity* across teams within a firm.[4] There are two disparate approaches to organizing technological diversity into teams within a firm: the diversity of inventors' technological experience can be distributed (i) within a team ("within-team diversity") and (ii) between teams in a firm ("across-team diversity"). Prior investigations into R&D team design have primarily focused on the level of diversity within teams (Choudhury and Haas, 2018; Hoisl et al., 2017; Reagans and Zuckerman, 2001).

Yet considering the level of knowledge diversity across teams is equally important

[4] In this paper, I remain agnostic about how teams are formed within a firm. The creation and management of teams vary across companies and industries. Companies like Hewlett-Packard or Motorola are known for allowing teams to form "organically" (Katzenbach and Smith, 1993); biotech and academia are examples of fields pushing for agile, self-forming, self-organized teams (Di Fiore et al., 2019). On the flip side, many firms design teams around relevant scientific domains or strategic initiatives. Regardless of how teams are formed, managers at firms have discretion over designing teams or, at a minimum, guiding employees on how best to create teams.

when considering the diversity of knowledge that exists at a firm (Aggarwal et al., 2020; Hansen, 2002).[5] Firms commonly encourage employees to build relationships outside their immediate teams, so as to share ideas and discover new collaboration opportunities. For example, Apple's new 'spaceship' campus has been lauded for promoting collaboration activities across units. The doughnut-shaped building allows employees to easily access members on the opposite side of the ring through the inside and outside perimeters. Rather than being stable and rigidly bounded, in recent years, teams have become more "fluid, overlapping, and dispersed" with blurrier boundaries (Mortensen and Haas, 2018). Thus, the knowledge an employee is exposed to and the extent of knowledge sharing at an organization are also dependent on the diversity of knowledge residing across different teams.

Figure 2.1 illustrates a hypothetical example of how knowledge diversity can be organized within a firm. The same set of inventors can be organized into teams with different levels of high or low within-team diversity and across-team diversity. Whether a firm has high versus low knowledge diversity is a function of the numbers of inventors, teams, unique technological fields, and, most importantly, the organization of inventors within and across teams. In the following section, I examine how the two types of knowledge diversity affect post-mobility innovation performance of external hires and their teammates.

[Figure 2.1]

[5] Although both Aggarwal et al. (2020) and this paper explore the link between the two diversity measures and innovation (measured by forward citations), each addresses a different question with distinct insights. Aggarwal et al. (2020) investigate how firms with diffuse structures (high within-team and low across-team diversity) and concentrated structures (low within-team and high across-team diversity) affect the *variation in overall firm-level innovation quality*, while the present analysis considers how the two diversity measures—factors exogenous to an externally-hired inventor's performance (given that firms do not change the firm-level team composition based on a single individual)—contribute to the *variation in the change in individual-level innovation performance following a mobility event.* Thus, the present paper proposes an important organizational design factor that can affect post-mobility performance of external hires and their teams, which in turn has implications for human capital management in technology-intensive organizations as well as for R&D team design.

Within-team Diversity

Firms can foster innovation by increasing the representation of diverse knowledge and experience within teams. To derive novel combinations of previously disparate technological domains, different and diverse knowledge must be both present and accessible (Fleming, 2001; Weitzman, 1998). I examine how the benefit and cost mechanisms proposed in Hypotheses 1 and 2—complementary knowledge, learning, adjustment costs, and coordination costs—are affected by the level of within-team diversity.

In terms of benefits, employees at firms with higher within-team diversity are more likely to be exposed to teammates who could complement their existing knowledge and skills. Thus, the knowledge benefit mechanism is likely to be stronger with a greater chance of developing new competencies and more creative recombination opportunities (Cohen and Levinthal, 1989; Makri et al., 2010; Singh and Fleming, 2010; Taylor and Greve, 2006). Second, a wider set of knowledge and skills could enhance members' learning capabilities—such as finding a novel solution, providing greater knowledge recombination opportunities, and avoiding groupthink (Gruber et al., 2013; Singh and Fleming, 2010; Taylor and Greve, 2006). Additional learning benefits accrue as members of diverse teams have broader social networks with indirect ties to other groups (Reagans and Zuckerman, 2001), thus enhancing the likelihood of creative and efficient technological solutions.

In terms of costs, members at firms with higher average within-team diversity experience greater difficulties in coordinating collaboration activities and integrating each other's knowledge inputs. As mentioned in the previous section, teams require coordination (i.e., common language, standardized routines) and such challenges could increase with members who possess more distant knowledge and fewer similarities in experiences and routines. However, the coordination conflict, which is a common challenge for all teams, whether they share similar or diverse knowledge bases, can also be minimized if they have an efficient division of labor and specialization (Ethiraj and Garg, 2012). Members of a team characterized by specialized knowledge can each focus on the relevant parts of the tasks or products. This specialized, collaborative work enables each member to develop expertise (Reagans et al., 2016). Furthermore, individuals on teams with high within-team diversity—those with more experience interacting with people with various knowledge backgrounds—will be better equipped to coordinate with new hires than those who have worked with similar others. Thus, the mutual adjustment and synchronization process among team members could be smoother at firms with greater within-team diversity.

The positive effect of within-team diversity on team performance has been well documented in earlier studies. Scholars have tested the hypothesis by exploring various sources of diversity and different organization outcomes, such as the effect of formal and informal organization unit membership diversity on patent scope and speed (Choudhury and Haas, 2018); the effect of job-related experience diversity and team efficiency (Hoisl et al., 2017); and the effect of demographic and network diversity on team productivity(Reagans et al., 2004). Although these studies consistently show that having a high level of diversity within a team is beneficial, I revisit this core hypothesis for three reasons. First, the effect of within-team diversity based on members' technological knowledge experience has not been tested with regards to employees' innovation performance. As I describe more in the empirical strategy section, I test the effect of within-team diversity on various innovation performance measures, including productivity, impact of inventions, creativity of inventions, and extent of learning. Second, the effect of within-team knowledge diversity has not been compared and contrasted with the effect of diversity across different teams. In the next section, I explain why the benefits of knowledge diversity are not realized if the locus of knowledge resides outside of the focal employee's team. Lastly, within-team diversity has not been tested with respect to external hires—the effects of within-team diversity on the external hire population could have a different direction or magnitude compared to the effect on the average incumbent employee at the firm. External hires, who have a more distant knowledge base than the average firm employee, may benefit more from greater complementarity of assets and learning. Alternatively, they may also incur greater costs with greater diversity, as adjustment costs and coordination costs for all team members add up.[6] Thus, I examine the relative effects of the firm's average within-team diversity on the external hire population and on their teammates separately.

Hypothesis 3a: *External hires who move to firms with higher levels of within-team knowledge diversity will, on average, experience higher innovation performance compared to those who move to firms with lower levels of within-team knowledge diversity.*

Hypothesis 3b: *Teammates at firms with higher levels of within-team knowledge diversity will, on average, experience higher innovation performance compared to those at firms with lower levels of within-team knowledge diversity.*

Across-team Diversity

Considering knowledge diversity as existing only within a bounded team does not completely capture the learning channels that may exist at an organization. Whereas within-team diversity exhibits the diversity level of successfully formed or "realized" teams, across-team diversity captures overall knowledge diversity across members in a firm. However, absorbing knowledge across a team is not as easy as within teams.

[6] In my empirical models, I observe the curvilinear effects of within-team diversity when the innovation performance is measured in terms of the likelihood of breakthrough innovation. For the other five outcome measures, I only find an accelerating upward curve or null effects on the squared term. The curvilinear effects don't appear until the extreme level of within-team diversity. It could be that firms might be mindful to combine people who are not too different from one another. Relatedly, firms might split groups of inventors with extremely heterogeneous knowledge base into several teams.

The locus of cross-team knowledge resides outside team boundaries and thus limits accessibility.

Knowledge diversity across teams could entail both benefits and costs. In terms of benefits, the knowledge-based view argues that the primary goal of a firm is to integrate the specialized knowledge of its employees (Aggarwal et al., 2020; Grant, 1996). Thus, the very purpose of a firm's existence may support having a high level of complementarity in the knowledge base existing between R&D teams. In examining patenting activities in optical disk technology, Rosenkopf and Nerkar (2001) find that knowledge exploration spanning technological and organizational boundaries has a greater technological impact relative to local searches.

Yet a high level of across-team diversity can pose *disadvantages* for employees for the following reasons. First, at firms with more across-team diversity, a focal employee has more distant knowledge experience and routines from other teams (Hansen, 2002), which could reduce knowledge spillover and learning benefits. The complexity of knowledge, that is, the degree to which a piece of knowledge comprises many elements requiring rich interaction or the level of difficulty recombining elements (Simon, 1991), could make a knowledge recipient resist knowledge transfer and, thus, reduce knowledge diffusion (Ethiraj and Levinthal, 2004; Sorenson et al., 2006). According to the absorptive capacity argument, prior possession of relevant knowledge and skills is what gives rise to creativity (Cohen and Levinthal, 1990). While existing knowledge that is too similar to acquiring knowledge may contribute little to learning and innovation, existing knowledge must at the same time be relevant enough that the diverse technological knowledge of collaborators can be absorbed and applied to generate new ideas. The lack of absorptive capacity may not be an issue for within-team diversity but for across-team diversity, given the assumption that the knowledge diversity from different teams becomes too distant and irrelevant for knowledge recipients to absorb and find relevant for their own use.[7] As information and routines become more dispersed, the cost for an individual to integrate knowledge increases, which in turn makes it more challenging to create new knowledge (Kogut and Zander, 1992; Mors, 2010). Scholars have shown that an organization's sub-units perform well to the extent that they retain related competencies that can be used across multiple sub-units (Hansen, 2002; Markides and Williamson, 1994).

Second, higher across-team diversity is associated with increased across-team coordination costs, as knowledge sharing is less likely to occur naturally or involuntarily. To take advantage of a diverse set of technological knowledge present across teams within a firm, an inventor must seek out and acquire information from others, then digest it for her or his own use (Cohen and Levinthal, 1990). Such costs are much higher at firms with high average across-team diversity. Prior literature on knowledge management finds that network connections facilitate knowledge transfers and synergies across a firm's business units (Kogut and Zander, 1992; Singh, 2005). For example, Singh (2005) provides evidence that intra-regional and intra-firm knowledge flows are stronger than those across firms and regions. Whereas knowledge sharing naturally and involuntarily occurs among members within a team,[8] an employee needs to conduct an active search process to access new information from socially distant actors (Hansen et al., 2005). These searches are even more difficult and costly for external hires, as they may initially lack the common skills, routines, and/or languages possessed by incumbent employees. Newly moved hires also have fewer social ties outside

[7]Table 2.1 shows that the the average knowledge distance between members within a team is, on average, much smaller than the distance between members across teams (0.50 vs. 0.76). The complexity of knowledge appears to be a bigger problem when considering diversity across teams than within teams.

[8]Fleming et al. (2003)'s field interviews suggest that patent collaboration teams meaningfully portray professional and personal ties among the inventors and that patent co-inventors often remain in touch even after applying for the patent. These ties are useful in the iterative knowledge search process: there are fewer errors when interpreting newly transmitted knowledge and a knowledge recipient can efficiently solicit advice from the knowledge provider (Sorenson et al., 2006). Moreover, these social ties contain tacit knowledge, a set of embedded knowledge distinct from explicit technological knowledge, such as common skills and shared language (Inkpen and Tsang, 2005; Lam, 2000; Polanyi, 1966)

of their own R&D teams. Besides the costs associated with searching and transferring knowledge, research suggests that interactions with members outside their own teams could interfere with internal coordination within teams (Hansen, 1999). Introducing external and diverse knowledge could make it difficult for teammates to agree when they integrate knowledge and make important choices for the invention. As such, a diverse set of knowledge allocated across teams may be detrimental for external hires and their teammates' learning.

Third, intensified competition across R&D teams could lead employees at firms with higher across-team diversity to experience more difficulties in knowledge production (Luo et al., 2006). Firms have constraints on key resources, including financial resources (e.g., R&D expenditure), human resources (e.g., workforce, number of R&D teams), physical space (e.g., workspace, production plants), and attention from senior management. Inter-team conflict could arise if the development of a team's R&D effort constrains the technologies and products of other teams (Hansen et al., 2005; Sorenson, 2000; Tsai, 2002). Teams working on developing new technologies for a product may also compete for technical or engineering specifications. For instance, at a smartphone manufacturing company, multiple R&D teams in the display, rear camera, speaker, and facial recognition technologies compete for component space on the display screen, in addition to R&D budget, personnel, strategic importance, and political power. The rivalry intensifies as teams are constantly compared to and benchmarked against one another. Thus, the competition could prevent communication and knowledge sharing between members of different R&D teams. The competition intensifies as more diverse and greater numbers of teams compete for limited resources. Thus, high across-team diversity is likely to disturb an employee's learning process.

For these reasons, external hires and their teammates at firms with higher levels of knowledge diversity across teams will not be able to reap the benefits of having a broad set of knowledge present at the firm.

Hypothesis 4a: *External hires who move to firms with higher levels of across-team knowledge diversity will, on average, experience lower innovation performance compared to those who move to firms with lower levels of across-team knowledge diversity.*

Hypothesis 4b: *Teammates at firms with higher levels of across-team knowledge diversity will, on average, experience lower innovation performance compared to those at firms with lower levels of across-team knowledge diversity.*

Understanding how different ways of designing R&D teams affect the extent to which its members contribute to the firm's innovation performance has been overlooked in the literature and by many firms alike. I treat team design characteristics—within-team diversity and across-team diversity—as given (or static) in the short-term at the time of the move. For instance, it would be difficult and costly for firms to change team structure with the arrival of one external hire. Also, adjusting team structure too often could be disruptive to the firm and deter coordination among employees. Thus, it is reasonable to assume that team structure remains rather stable at least in the short term. However, I posit that team structures could be improved by managers at the firm in the long run. After I test my hypotheses, I further discuss how firms could more efficiently restructure and assign new hires into incumbent teams.

2.3 Empirical Strategy

2.3.1 Patent Data and Mobility

Understanding the link between mobility and knowledge flows presents empirical challenges, as researchers need comparable performance records before and after a move, as well as observations on a large number of individuals working in the same field. Longitudinal data of detailed career histories are necessary to investigate changes in employee performance following a mobility event.

Patent data provide an attractive source of fine-grained information on each patent, including inventor and assignee firm names, application and grant dates, technological classifications, and backward and forward citations (Choudhury and Haas, 2018; Gruber et al., 2013; Mowery et al., 1996; Palomeras and Melero, 2010; Singh and Agrawal, 2011; Somaya, 2012). These data bring several advantages to investigating my research questions. First, patent data provide historical accounts of inventors' past experiences, thus allowing researchers to track career histories. Although exact move dates are not readily available, researchers can infer mobility by chronologically tracing patents applied by each individual. Second, patent citation and classification data offer several measures of innovation performance. Future citations provide a systematic means of measuring the impact of an inventor's patent. The number of patents during a given period can serve as a measure of productivity. In addition, the number of unique technological fields and the technological diversity of an inventor's patents can capture the extent of learning and novelty of inventions. Third, the large sample of inventors who move to a different firm at least once across a wide range of technology sectors increases the power of statistical tests while also rendering the results more generalizable than studies focusing on firms in a single sector.

2.3.2 Constructing an Employee Mobility Dataset

I use publicly available United States Patent and Trademark Office (USPTO) data to examine the link between designing teams and innovative outcomes. This dataset contains information on all granted patents since 1975. While inventor and assignee firm names are available for each patent application, the data from USPTO do not offer a unique identifier for each inventor and assignee firm. Supported by the USPTO

Office of the Chief Economist, the PatentsView website (www.patentsview.org) provides a reliable source for firm, inventor, and location disambiguation data based on algorithms devised by a team of scholars studying intellectual property, innovation, and technological change.

To detect mobility events, I track changes in firm identifiers on an inventor's successive patents (Almeida and Kogut, 1999; Singh and Agrawal, 2011; Song et al., 2003). I start with the sample of all U.S. utility patents from 1975 to 2017 and then chronologically trace applied patents. I restrict the sample to patents with a single firm, as it is difficult to infer the employer of an inventor if there are multiple assignee firms for a patent. The sample is limited to inventors who have moved between U.S. companies or corporations and does not include those who have worked for the government or as an independent inventor. From there, I construct a list of inventors who have moved firms at least once.

Even when I observe two successive patents by the same inventor but at different firms, I cannot pinpoint the exact move date. Since my key variables are based on the inferred move date, results can be sensitive to the move window estimation. To overcome this challenge, I adopt Singh and Agrawal (2011)'s approach: the move date is defined as the halfway point between the last patent application date at the previous firm and the first application at the new firm. I drop cases with move windows of four or more years, as the move date is too uncertain.[9] This results in an initial set of 437,383 inferred mobility cases.

Given the uncertainty that the move could have taken place any time during the window, I use the calendar year of the inferred 'move date' estimate. Then, I remove mobility events in which an inventor has spent less than one year at either the departure firm or the destination firm. This restriction ensures a sufficient observation period to calculate performance metrics at both firms, yet leads to dropping about

[9] In addition to removing observations with uncertain move dates, I also control for move windows in my models.

60 percent of the initial set of the mobility cases, resulting in a new total of 166,408 observations. As a final step, I remove mobility events with the end date at the destination firm after 2012 to enable the calculation of five-year forward citations of post-mobility patents. The resulting mobility sample consists of 120,549 mobility observations corresponding to 78,287 inventors at 27,933 firms.[10][11]

Patent data and our focus on external hires are subject to several potential selection biases. First, by observing a set of inventors who have successfully moved to different firms with at least one patent in their second jobs, I may be systematically ignoring other types of inventors, like those with lower innovative productivity. Second, firms make deliberate choices about whom to recruit and so may prefer to hire inventors more likely to improve diversity and/or performance. Third, inventors may sort themselves into firms with certain types of diversity. To account for these selection concerns, I conduct a matching study in which I include the sample of "non-movers" (further described in the following section).

2.3.3 Matching Approach to Measure Post-mobility Innovation Performance

While existing studies have primarily focused on firm-level outcomes to capture the effect of mobility, I focus on the post-mobility performance of external hires and their teammates. I examine the post-mobility performance based on each individual's

[10] Although the final sample is 30 percent of my initial sample of mobility events, I do not expect my results to be systematically different. Rather, including cases in which inventors have spent less than a year at the departure or destination firm could bias my estimates, as early departure may be correlated with performance at the firm. That is, inventors with short tenures could be superstars frequently poached by firms or low-quality inventors who are laid off. Research and patent applications typically take at least a year, thus patent outputs for these inventors could appear to be zero even if the inventor played an active in a new invention. Removing events after 2012 should not affect the results. I include move year fixed effects in all of my models to account for time trends.

[11] The final sample used for analysis consists of 63,976 mobility cases. The sample size is reduced while calculating two firm-level team diversity measures and control variables, which I will further describe in the Measures section.

knowledge production (i.e., patenting) activities after the mobility event accounting for pre-mobility performance differences (Hypotheses 1–2). Then, I consider how a firm's team design structure moderates the performance change (Hypotheses 3–4). If mobility occurs in time t, I measure the post-mobility performance from time $t+1$ and the pre-mobility performance until time $t-1$; the team design characteristics and control variables are measured at time t.

Examining an individual's post-mobility performance offers several methodological advantages. First, I can disentangle an external hire's performance contribution from knowledge spillover effects to teammates. Singh and Agrawal (2011) demonstrate that both recruits' exploitation of their own prior ideas, as well as diffusion to others, are simultaneously captured in firm-level outcomes. Measuring the contribution of external hires at the team- or firm-level may lead to an overestimation of the outcome. Second, when both explanatory variables and outcome variables are measured at the firm level, there can be potential endogeneity issues. An unobserved variable, such as a firm's corporate strategy (e.g., acquisitions, geographic expansion), may explain variations in both team diversity measures and the firm's innovation performance. Since I compare an inventor's performance before and after a mobility event, the change in performance associated with R&D team design is less likely to be affected by the firm's strategic efforts when observed at the individual level.

For external hires, I compare the post-mobility performance at the destination firm throughout the hire's tenure, taking into account their performance at the departure firm. Further, I compare the post-mobility performance of external hires with "non-movers." Specifically, I use a matching strategy to identify a set of "non-movers," or incumbent employees with similar characteristics to external hires but who do not switch firms. I construct the"non-movers" group from a pool of inventors who have worked at the focal mover's departure firm between the mover's start and end dates at the destination firm. Next, I select those who worked on the same technological field as the focal hire using NBER sub-category at the time of the move. Then, I use the nearest neighbor matching strategy, based on the number of patents produced over the past five years before the move date.[12]

To capture how an external hire brings knowledge spillover benefits to teams, I examine how mobility affects the new hire's teammates. While it would be ideal to observe performance change at the team-level, team membership is typically not stable across time within a firm. For example, teams are often assigned on a project-basis and so the same set of inventors typically do not appear more than once. Thus, I explore how the focal hire impacts teammate performance after the mobility event. More specifically, I randomly select one of the earliest teammates who collaborates with the new hire and then assess how the teammate's innovation performance changes after collaborating with the focal inventor.

To arrive at a more precise estimate for the spillover effect from the focal inventor to the team, I examine the post-mobility performance difference between teammates and the counterfactual group of randomly selected employees ("non-teammates") at the same firm who do not directly collaborate with the focal hires. I compare how teammates versus non-teammates perform during the two years after the focal inventor joins the firm, controlling for two-year performance prior to working with the new hire. I chose the two-year time frame as the main model because many inventors in my sample move within three years (approximately 65 percent of my sample) and longer windows bring more noise to my estimation.[13] Nonetheless, I show results with outcomes measured over the two-year, three-year, and throughout tenure at the firm. Since teammates, compared to non-teammates, could systematically differ in terms of their attributes and performance, I control for individual characteristics including prior performance.

[12]The missing pairs are due to inventors without the same firm and technological expertise.

[13]Observing performance during each teammate's tenure at the focal firm could bring noise into my estimation, as individuals who stay longer than two years at an organization would be exposed to many external hires, and it would be difficult to capture the focal inventor's contribution.

2.3.4 Measures

Innovation Performance

Firms have different strategic goals and preferences for how to improve innovation performance. For example, some firms apply for as many patents as possible in order to demonstrate market dominance in a given technology sector. Other firms focus on producing one "breakthrough innovation," emphasizing singular quality over quantity. Thus, I consider a variety of outcomes to inform the specific ways in which R&D team design affects the innovation process of inventors. Specifically, I have six variables that capture innovation performance.[14] The first dependent variable, *number of patents*, serves as a proxy for productivity and measures the count of all patents produced after a mobility event.

The number of forward citations has been widely used as a measure of the technological impact and economic value of a patent invention (Jaffe and De Rassenfosse, 2017). I derive *forward citations* using the number of forward citations received within the five-year post-application period for each patent and then calculating the average of the counts. The distribution of citation counts ranges from 0 to 1,051, has a median of 6.4, and is heavily skewed to the right. Thus, in addition to considering *average* citations, I also consider the *distribution* of citations—specifically, "breakthrough" innovations and those with minimal impact (Singh and Fleming, 2010). I create two binary variables: *top 5 percent cite* and *zero cite*. *Top 5 percent cite* takes

[14] While most of the dependent variables are not highly correlated with each other, I find strong correlations between (1) the *number of new tech classes* and *number of patents* ($\rho = 0.66$) and (2) the *number of new tech classes* and *tech diversity* ($\rho = 0.60$). This is not surprising given that the new technological class acquired is associated with the number of patents produced at the new firm. Yet the two outcomes have different implications: productivity at the destination firm for the former and the degree of learning or acquisition of new technical knowledge for the latter. Also, the *number of new tech classes* is strongly linked with *tech diversity*, because the technological diversity calculation is dependent on the total number of technological classes. While the *number of new tech classes* informs the extent of learning at the destination firm, *tech diversity* serves as a measure for the novelty of the patents. I explore the six innovation performance measures separately, as each performance measure has distinct strategic implications for firm strategy. The correlation table can be found in Table 2.2.

a value of one if at least one of the patents produced at the destination firm is in the top 5 percent of five-year forward citations in a given application year and technology class.[15] *Zero cite* is set to 1 if all of an inventor's post-mobility patents receive no citations.

To examine the breadth of technological fields capturing the extent of *learning* and *novelty* of patents, I construct two additional dependent variables: *tech diversity* and *number of new tech classes*. *Number of new tech classes* measures the number of new technological fields the inventor has entered after joining the new firm, while *tech diversity* measures the degree of technological recombination. I follow the previous literature and use 1 minus the Herfindahl Hirschman Index (HHI) of concentration of post-mobility patents across different technological classes (Marx et al., 2009; Trajtenberg et al., 1997). For an inventor i with J patents that are associated with technological areas $k = (1, \cdots, K)$, the diversity measure using HHI can be defined as:

$$Tech\ Diversity_i = 1 - \sum_{k=1}^{K} \left(\frac{\sum_{j=1}^{J} s_{jk}}{J}\right)^2,$$

where s_{jk} is the patent j's share of technology classifications associated with technological area k. HHI corresponds to the sum of squared shares of technological fields across an inventor's post-mobility patents. If all of the patents build on knowledge from one patent class, technological diversity is equal to zero; it approaches one as the patents cited are spread across more technological fields.

Within-team Diversity and Across-team Diversity

The two firm-level team design factors are *within-team diversity* and *across-team diversity*. These two measures capture how the technological knowledge experience of inventors is allocated within and between R&D teams. The team

[15]The average top 5 percent cutoff point for five-year forward citations of patents in the sample is 75

diversity variables are measured at the move year in order to ensure that team compositions do not change based on new hires.[16] Within-team diversity of a destination firm captures the average dyadic diversity in technological fields *between inventors* within a given patent team. Across-team diversity measures the average dyadic diversity in technological fields *between teams*, showing how teams differ from one another in terms of employees' knowledge experience. A detailed description of how I compute the measures, as well as an illustrative example can be found in Appendix B.

To calculate *within-team diversity*, I measure the angular distance between the knowledge experience vector of each pair of inventors within a team. The knowledge experience vector contains the count of patents produced in each technology category. I consider all technology experience gained throughout an inventor's career.[17] Then, I take the average of each patent team's team-level value to come up with firm-level average within-team diversity. For *across-team diversity*, I calculate the angular distance between the knowledge experience vector of each pair of patent teams within a firm. Instead of calculating a vector for each individual, I create a knowledge experience vector for each team, adding up the teammates' experience in technological fields throughout their careers. To calculate firm-level average across-team value, I take the average of the pairwise distance between each pair of teams.

I identify R&D teams as sets of inventors who file for the same patent application (Aggarwal et al., 2020; Jensen et al., 2018; Singh, 2005; Singh and Fleming, 2010). R&D team memberships are observed when the patent application is submitted, though there may be other teams at a firm collaborating on a project not

[16]These measures are calculated over a focal inventor's move year window, rather than calculating them over their tenure time at the destination firm (the window used to calculate the outcome variables) to minimize endogeneity concerns, which arise when firm strategy or performance may be linked with both team diversity and an individual's post-mobility outcome.

[17]I capture an inventor's knowledge base using three-year and five-year career trajectories. Yet capturing knowledge base during the short-term does not completely reflect the stock of knowledge. I observe similar patterns, with larger magnitudes of the coefficients for the diversity measures, when using inventors' entire trajectories. Thus, looking at the entire stock of knowledge accumulated throughout one's entire career appears to offer the most robust proxy for understanding the diversity of knowledge existing in a team (or a firm, for *across-team diversity*).

reflected in the data. Interviews with patent inventors and patent agents at law firms confirmed that the list of inventors in a patent application represents a typical R&D team within a firm.

In Figure 2.2, I illustrate the distribution of within-team (x-axis) and across-team diversity (y-axis) measures, which both range from 0 to 1, in my sample.[18][19] As shown in the scatterplot, firms are dispersed across the four quadrants. Here, I also provide examples of firms engaging in R&D activities in the semiconductor technology (NBER sub-category of 46) with high or low within-team and across-team diversity. Among firms conducting research in the semiconductor space, the average within-team diversity score is 0.47, while the average across-team diversity score is 0.71 (the average scores of within-team and across-team diversity measured in the entire sample are 0.44 and 0.62, respectively, as shown in Table 2.1).

[Figure 2.2]

Control Variables

Pre-mobility performance. To capture the change in an external hire and their team-mate's performance after mobility, I use post-mobility performance as the dependent variable and control for pre-mobility innovation performance. Since each dependent variable reflects different ways of understanding innovation performance, I include a pre-mobility performance control relevant for the specific dependent vari-

[18] Missing values occur in two cases. First, I cannot calculate diversity measures if a firm's number of patents or number of inventors in a move year is less than 2. Second, diversity measures cannot be calculated if the number of previous patents by an inventor is less than 2 and if there is only one inventor with previous patents; in this case, the diversity score will automatically be zero. Thus, these observations are marked as missing rather than showing up as zeros. There are 74,512 observations with complete within-team diversity measures, 69,095 observations with across-team diversity measures, and 69,095 observations with both diversity measures. This represents 5,408 unique firms, which have on average 9.5 R&D teams (median of 2) filing for patents each year. There are, on average, 2.9 members on each R&D team.

[19] The partial correlation (applying control variables, move year and industry fixed effects) between the two diversity measures is between 0.3 and 0.4. I conduct analyses using the two diversity measures together in a model and separately in different models to ensure that the correlation between the two variables is not driving the results.

able. For models with post-mobility number of patents as outcome variables, I use *pre-move number of patents* to account for the innovation productivity at the departure firm. For the three dependent variables that use forward citations, I use *pre-move forward citations*, average forward citations of patents produced at the prior firm. I include *pre-move number of tech classes* and *pre-move tech diversity* for models on post-mobility *number of tech classes* and *tech diversity*, respectively.

Destination firm characteristics. I control for several firm-level characteristics that can simultaneously influence mobility, team design, and innovation performance. Instead of measuring these firm characteristics during the move year, I take the average over a three year window, from one year before to one year after the move year. This approach smooths out potential noise from year-to-year fluctuations.[20] I measure *firm age* as the number of years since a firm's first patent application date; *firm size*, the total number of patents applied; *firm number of inventors*, the unique number of inventors; and *firm scope*, the number of unique technological (main) classes of the patents produced at the observed year. Team size could affect the diversity level and performance, thus I control for *firm team size*, the average team size for all patent teams applied at the observed year.[21] Inventors who join firms with a high level of growth could appear to be more productive because the firm is growing faster than average. Thus, I also control for *firm growth rate*, measured using a 3-year compound annual growth rate (CAGR)—one year before the mover year as the beginning year and one year after the move year as the end year—of patents produced at the destination firm.[22] The organization of R&D across geographic spaces is an important determinant of firm-level innovation (Chacar and Lieberman, 2003). I also control for *firm geodiversity*, or the degree of geographic

[20]Comparing these results to those using the move year based measures produces similar estimates.

[21]I also tried using the average number of members in patent teams of each focal inventor and find similar estimates.

[22]Using a 5-year CAGR, highly correlated ($\rho = 0.90$) with 3-year CAGR, also yields consistent results.

diversity (or concentration), calculated using the Herfindahl index (based on equation 2.3.4 to examine the distribution of R&D locations at the state level).

Mobility characteristics. To enable a systematic comparison across different inventors with varying tenures at their departure and destination firms, I control for *tenure at destination* and *tenure at departure*, measured as the number of years an inventor spent at the destination firm and departure firm, respectively. I also control for an inventor's *R&D Experience*, or the number of years since an inventor's first patent application date. I also control for *move window*, the time period between the last patent application filed at the departure firm and the first patent application filed at the destination firm, to account for the increased uncertainty with longer move windows.[23]

Table 2.1 and Table 2.2 present the summary statistics and pairwise correlations. For 63,796 external hires in my sample, I was able to find 31,056 pairs of teammates and non-teammates.[24] Table 2.3a shows team knowledge diversity statistics by three key firm characteristics: firm size, average team size, and firm patent growth rate. Table 2.3b depicts how team composition varies by team diversity.

[Table 2.1]

[Table 2.2]

[Table 2.3]

[23]Inaccurate midpoint estimations may systematically bias the estimates. The coefficient should be close to zero if the inferred move year is accurate; negative if, on average, the actual entry to the destination firm is earlier than the inferred move year; and positive if, on average, the actual entry to the destination firm is later than the inferred move year.

[24]There are missing teammate and non-teammate pairs if the focal inventor does not have more than one patent or does not have a collaborator at the destination firm (approximately twelve percent of the sample). The teammates or non-teammates who joined after the focal inventor or who left before the focal inventor also had to be removed.

Preferred Regression Models

The two dependent variables, *number of patents* and *number of tech classes*, are measured as counts and are skewed to the right. Counts cannot fall below zero, thus linear regression models may yield inefficient and biased estimates. I use poisson quasi-maximum likelihood estimator (QMLE) for these variables.[25] The default log-link function is used for quasi-poisson distribution, so I log the continuous independent variables for ease of interpretation. This allows me to interpret the coefficients as elasticities. For continuous dependent variables, I use ordinary least squares regression models. For the model using average forward citations, I employ log-log regression: the dependent variable is logged as the distribution is heavily skewed to the right; the explanatory variables are also in log form for constant elasticity.

For all models, I employ robust standard errors clustered at the destination firm level. I also add move year and technology fixed effects. The move year dummies are used to control for the difference in the calendar year in which employees move to another firm. Since mobility and citation patterns may vary substantially across different technological fields, I include the National Bureau of Economic Research (NBER) technology area subcategory as dummy variables.[26] For individuals who have worked on multiple technological fields, I chose the last technological field that a focal inventor has worked before the mobility event, which should be reflective of the technology or industry that they will work on at the new firm.

[25] Scholars have commonly employed poisson or negative binomial models for estimating parameters. Compared to negative binomial model, the poisson model is more robust to distributional misspecification if the conditional mean is correctly specified (Cameron and Trivedi, 2013). The poisson model, however, relies on a strong assumption that the conditional mean and variance are the same. In my data, the variances of dependent variables are larger than the means. Thus, the poisson quasi-maximum likelihood estimator (QMLE), which relaxes the assumption of the classic poisson model and better accounts for the over-dispersion parameter, is employed (Kang and Lee, 2018).

[26] Using World Intellectual Property (WIPO) technology fields or cooperative patent classification (CPC) for technology field dummies yields similar results.

2.4 Results

2.4.1 Post-mobility Performance of External Hires and Teammates

Table 2.4 shows the results for Hypothesis 1, which tests whether external hires suffer from performance gains or losses after mobility throughout their tenure at the new firm. The models show the differences in the post-mobility performance of external hires compared to "non-movers." My results suggest that external hires have 92.5 percent greater productivity ($e^{0.655} - 1) \times 100$), 23.4 percent fewer average forward citations, 19.7 percent greater number of technological fields learned, and greater novelty of patents. These estimates are significant at the 5 percent level. Overall, mobility has a positive effect on innovation outcomes, except for the distribution of citations (the likelihood of breakthrough innovation decreases by 1 percent and the likelihood of producing zero-impact patents increases by 3 percent). Although the effect sizes for these outcomes are small, one possible explanation for the negative trend is that external hires may sacrifice their creativity while working on producing more inventions with new colleagues.

The findings are largely in line with the research on post-mobility individual performance in knowledge production contexts (Hoisl, 2009; Tartari et al., 2020) that mobility has a positive impact on individual performance. Some studies have suggested a negative relationship, known as the "portability of performance paradox" (Bidwell, 2011; Campbell et al., 2014; Groysberg et al., 2008; Raffiee and Byun, 2019). However, the mechanisms that these studies propose, such as firm-specific human capital and person-organization fit concerns, appear to be less disruptive for innovative talent characterized by more transferable of human capital (i.e., patent inventors, academics).

[Table 2.4]

Table 2.5 reports the findings for Hypothesis 2, which addresses how external hires affect the performance of their teammates. The sample contains the matched pairs of teammates and non-teammates. In Panels A and B, I compare post-mobility performance of teammates compared to non-teammates two years after the focal inventors' move, before and after controlling for prior performance, respectively.[27] The coefficient for *Teammate* indicates the post-mobility performance differences between teammates, compared to non-teammates. Even after controlling for prior performance, teammates, compared to non-teammates, produce 5.1 percent fewer patents ($(e^{-0.052}-1)\times 100$). The productivity decline may be associated with the costs associated with working with external hires: that collaboration with an external hire entails significant coordination costs. Yet conditional on having at least one patent produced, the quality of patents improves, specifically the average forward citations increases by 12.3 percent and the likelihood of breakthrough innovation increases by 2.4 percent (both significant at the 1 percent level).

Panels C and D show the performance change over the three-year window and throughout the teammates' tenure at the firm. For Panel D, the sample includes teammates who may have spent less than two years or more than two years at the firm. Teammates, on average, spend 5.7 years at the destination firm, thus the panel shows the mobility effect on longer-term performance. After two years, teammates are able to recoup their productivity (model 1). Estimates of the other performance metrics also show that teammates perform better than non-teammates who don't collaborate with the new hires.

[Table 2.5]

In Table 2.6, I further investigate the effect of knowledge spillover from external hires to teammates by examining whether the newly acquired technical knowledge

[27]Randomly selected earliest teammates and non-teammates share different pre-mobility characteristics.

of teammates relates to the knowledge learned from the external hires. In model 1, I do not find any systematic difference between teammates and non-teammates in the absolute number of any new technological classes acquired during the two-year period. However, teammates, compared to non-teammates, learn 21 percent more technological knowledge that they did not previously possess but the hires had, providing evidence of direct knowledge transfer from the focal hire to teammates (model 2). Furthermore, I discover that the knowledge spillover effects are greater when the hires are at firms with higher within-team diversity (model 3) and paired with a teammate with greater dyadic knowledge distance (model 4). The moderating effects of team design will be further examined in the next section.

[Table 2.6]

2.4.2 Team Design and Post-mobility Performance

Table 2.7 provides results related to Hypotheses 3 and 4 regarding the two types of knowledge diversity.

Panel A of the table reports the moderating effect of firm-level team diversity on the performance of external hires. The coefficients of the knowledge diversity measures explain how the two design factors contribute to the post-mobility performance of external hires and their teammates.

For external hires, Panel A models 1 to 6 suggest that a one standard deviation increase in within-team diversity is associated with: a 0.8 percent increase in the likelihood of creating "breakthrough" innovation ($\frac{0.021\times0.16}{0.44\times0.01}$), a 2.5 percent increase in the technological domains learned at the new firm, and an increase in combination novelty of patents (significant at the 5 percent level). In contrast, a standard deviation increase is across-team diversity is associated with: a 0.6 percent lower productivity ($\frac{-0.015\times0.26}{0.62\times0.01}$), a 3.0 percent fewer average of five-year forward citations of patents produced at the destination firm, a 2.3 percent decline in the likelihood of "breakthrough" innovation, a 2.0 percent greater chance of not receiving any citation, and a small decline in learning new technological fields and combination novelty of patents (all significant at the 1 percent level).

Panel B of Table 2.7 shows that the two diversity measures have a similar impact on the two-year post-mobility performance of teammates. For external hires, a one standard deviation increase in within-team diversity is associated with: a 2.3 percent decline in the likelihood of producing only zero-impact inventions, a 3.2 percent increase in the number of new technological classes learned, and a greater combination novelty of patents produced (significant at the 5 percent level). A one standard deviation increase in across-team diversity is linked with: a 1.2 percent decrease in the number of patents produced, a 1.7 percent increase in the average citation impact, a 0.7 percent increase in the number of new technological fields learned, a 3.8 percent increase in the likelihood of breakthrough innovation, and less combination novelty of patents produced (significant at the 1 percent level).

Comparing Panel A and Panel C, which show the effects of the firm-level diversity measures on the performance of the two inventor populations throughout their tenures at the firm, I do not find any evidence that the impact of knowledge diversity of one population is substantially greater than the other. Yet my results suggest that the two dimensions of diversity measures have a strong and consistent influence on employees' post-mobility innovation performance, especially when the outcomes are conceptualized as the number of patents, the likelihood of creating a "breakthrough" innovation, the number of new technological knowledge learned, and the combination novelty of the patents at the firm compared to performance prior to the move.[28] The differing impact of within-team and across-team diversity informs managers that, to maximize the innovation performance of inventors within a firm, they should sepa-

[28]In unreported regressions, I include within-team and across-team diversity in separate models to ensure that the correlation between the two main independent variables is not driving the results. I observe congruent results across all innovation measures, despite slightly smaller coefficients.

rately consider two types of diversity when structuring their R&D teams.

[Table 2.7]

To assist in the interpretation of the results, I demonstrate what a one standard deviation change in within-team diversity and across-team diversity would look like in practice in Appendix B. Specifically, returning to the stylized example I provide in Figure 2.1b (Firm B), I illustrate two scenarios: (1) an external hire with "star" technology and (2) an external hire with "circle" technology joining Firm B and becoming a member of the first team (with two "circle" members and one "triangle" member). I then describe how each scenario shifts the two team diversity measures.

2.4.3 Additional Analyses

I conduct several additional analyses to examine the underlying mechanisms for knowledge diversity and to address possible endogeneity issues.

Dyadic Knowledge Distance

Conditional on hiring a recruit, how should the firm assign the hire to existing teams? In developing Hypothesis 3 on within-team diversity, I suggested that firms with higher within-team diversity promote greater knowledge benefits to external hires and their teammates, due to an increase in complementary knowledge assets. If so, we would expect assigning external hires to teammates with greater *dyadic knowledge distance*, compared to those with a similar knowledge base, would enhance the knowledge benefits to both the hires and the team constituents. The greater the dyadic knowledge distance, the more likely each member will provide new insights to the other member. Also, the distant knowledge base further allows greater idea recombination opportunities, thus increasing the likelihood of producing novel patents (Levinthal, 2016; Levitt and March, 1988; Maliranta et al., 2009). Examining the effect of knowledge distance thus allows me to confirm the underlying mechanisms for the hypothesis.

I calculate the dyadic knowledge distance between an external hire and their teammates (or non-teammates) by using the cosine similarity measure (equation 2.7) between the two individuals, and then subtracting it from 1 to calculate the distance. Table 2.8 shows that the post-mobility performance change of both external hires (Panel A) and their teammates (Panels B and C) increase with greater dyadic knowledge distance at the time of the move. Panel A shows that an increase of one standard deviation in the knowledge distance can result in 1 to 3 percent greater increase in new hire innovation performance ($p < 0.01$ except for in model 2).[29] Panel B shows that a one standard deviation increase in knowledge distance improves teammates' post-mobility performance by 3 to 9 percent ($p < 0.01$ for all estimates). It is important to note that assigning external hires who possess more distant knowledge, relative to more similar knowledge, can mitigate the productivity loss (shown in model 1 of Table 2.5). Specifically, a one standard deviation increase in knowledge diversity produces, on average, a 3 percent increase in immediate collaborators' short-term productivity. Also, an external hire with greater knowledge distance allows immediate collaborators to create more novel and valuable inventions.

[Table 2.8]

Endogeneity Considerations

My empirical strategy disentangles individual contributions from overall spillovers to a firm, overcoming endogeneity concerns that arise when both explanatory and response variables occur at the firm level. However, several endogeneity concerns remain, especially related to my analysis on team design. To address these potential issues, I conduct a number of robustness checks.

[29] The mean and standard deviation of the knowledge distance between external hires and teammates are 0.50 and 0.36.

Sorting of external hires. One potential concern is that external hires can choose to move to a more diverse firm and that this preference may be linked with performance. To examine the degree of self-sorting, in Table 2.9, I assess whether external hires with certain pre-mobility characteristics systematically select into firms with high or low levels of within-team and across-team diversity. I find a minimal (near-zero) effect of sorting. In addition to the small effect sizes, individuals select into firms with high levels of both within-team and across-team diversity. Thus, self-sorting does not appear to drive the variation in performance change stemming from knowledge diversity at the destination firm.

[Table 2.9]

Selection on hiring. Another endogeneity concern relates to the possibility that firms make deliberate choices about whom to recruit. That is, they may strategically hire inventors based on their performance or those who could improve the firm's diversity, biasing estimates on the moderating effects of team diversity structure. Analyses from Table 2.9 mitigate the concern that firms strategically hire to create more or less diverse team structures. Inventor performance before the move does not meaningfully predict the diversity level at the destination firm. Nevertheless, to further address the concern, I run the same models, as in Table 2.7 Panel A, for the two populations: external hires and "non-movers." Only new hires are affected by the new R&D team structure at the new firm, while "non-movers" are exposed to the same team design structure throughout their tenure at a given firm. If firms are strategically hiring based on an inventor's quality to improve team diversity, within-team diversity or across-team diversity would not systematically affect an inventor's post-mobility performance. Table 2.10 Panel A shows that even after accounting for matched "non-movers," the effects of within-team and across-team diversity are robust and consistent. While my matching strategy is not perfect and does not guarantee that the characteristics of moving and non-moving inventors are identical, the consistent estimates, even after adding the non-moving inventor sample, provide strong support that R&D team is an exogenous factor that can significantly enhance or weaken an inventor's performance following a move.

[Table 2.10]

Selection on mobility. One could argue that the estimates are biased because inventors do not move at random, and that those who possess certain characteristics (e.g., productivity, experience) move to carefully chosen firms. For my analysis on the post-mobility performance of external hires and their teammates, I control for prior performance of the individuals. For my analysis on team design, I am less concerned about the fact that inventors who move are systematically different from those who stay at one firm. My research question is centered on the population of employees who move at least once (and those who collaborate with them); 44 percent of inventors in the U.S. move at least once. While there may be self-sorting based on the overall productivity of an inventor, it should not affect the variation in *change in performance* stemming from team diversity at the destination firm. In fact, Table 2.10 Panel A shows that the effects of within-team and across-team diversity persist even after the "non-mover" sample is added to the models. To further test the generalizability of the results to the larger inventor population and to examine whether the two diversity measures affect inventors with and without mobility experience at similar magnitudes, I conduct a triple difference approach.[30] Table 2.10 Panel B depicts the interaction effects between the binary variable *External Hire* and the two diversity measures. The interactions between *External Hire* and the two diversity measures are not statistically significant, indicating that the "movers" and "non-movers" are similarly affected by knowledge diversity.

[30] I call it a triple difference approach, as the analysis in Table 2.7 can be described as an individual-level difference-in-difference, with time as the first difference and team structure as the second difference. Here, the third difference is the mobility decision.

2.5 Discussion

Management consulting reports and the popular press highlight the ever-competitive war for talent in knowledge-intensive organizations (Burgess, 2018; Kaplan et al., 2012; Smith, 2018). One highly publicized example is Apple and Tesla poaching each other's employees. A report shows that Apple pays up to a 60 percent wage premium to recruit human capital from competitors (Higgins and Hull, 2015). Although the poaching could be driven by ulterior motivation (e.g., to steal critical human capital from competitors), it would be an imprudent decision for a firm given the high costs of hiring. Rather, the talent war is more likely to be driven by accessing valuable external knowledge. In contrast to rising interest among practitioners on how to invest and manage human capital resources, relatively little research has examined whether external hires bring knowledge benefits to the firm, and if so, how they improve firm-level innovation through knowledge sharing with other employees. This paper aims to shed light on this question by assessing whether external hires improve teammate performance. In addition, I identify an important firm characteristic—R&D team structure—that facilitates knowledge sharing and enhances the innovation capabilities of the hires and their teammates.

Based on my sample of U.S. patent inventors' mobility events, I find that external hires experience an improvement in innovation performance following a move, consistent with extant studies that document the effect of mobility in knowledge production contexts (Hoisl, 2007, 2009; Tartari et al., 2020). Yet I also discover an interesting trade-off in the quantity and quality of teammates' innovation performance. Compared to "non-teammates" who never collaborate with the focal hire, teammates experience a reduction in productivity (i.e., number of inventions). However, if they successfully create a patent, they are more likely to create inventions with greater technological impact. The post-mobility performance of external hires and their teammates is contingent on how teams are structured. While within-team diversity has a positive impact on innovation performance, across-team diversity worsens innovation performance. Assigning an existing employee to a team with an external hire who possesses a more distant knowledge background can mitigate productivity losses and improve the quality of inventions produced.

My findings broadly contribute to three different streams of research. First, I contribute to the mobility and innovation literature by distinguishing the performance contribution of the focal hire and the performance ramifications for team members. Prior research on the knowledge spillover has primarily focused on firm-level outcomes (Almeida and Kogut, 1999; Arrow, 1962; Rao and Drazin, 2002; Samila and Sorenson, 2011; Saxenian, 1994). In this paper, I distinguish the performance contribution of an external hire and how they contribute to their teammates' innovative capabilities. Specifically, this study illuminates the process and extent to which the performance of teammates is affected. Earlier studies, especially from the "learning-by-hiring" literature, have expanded our knowledge on how firms benefit from hiring through the *exploitation* of the recruits' prior inventions (Corredoira and Rosenkopf, 2010; Palomeras and Melero, 2010; Rosenkopf and Almeida, 2003; Singh and Agrawal, 2011; Song et al., 2003). However, it remained unclear how an external hire affects the *exploration* activities of immediate collaborators through future knowledge production (Mawdsley and Somaya, 2016) after working with the hire. I find an interesting result that has not been documented in the literature: there is a trade-off in the immediate collaborators' quantity and quality of innovations. Thus, this study illustrates different ways in which external hiring affects the innovation performance of a firm's broader human capital.

Second, I highlight the importance of considering the effect of R&D team design on innovation. Understanding the critical role of collaborative teams in driving innovation within firms (Edmondson and Harvey, 2018; Mortensen and Haas, 2018; Singh and Fleming, 2010; Taylor and Greve, 2006; Wuchty et al., 2007), scholars have explored how different ways of structuring teams affect organization outcomes (Choudhury and Haas, 2018; Hoisl et al., 2017). Yet we know little about effectively assigning and integrating new hires into teams (Mawdsley and Somaya, 2016). Understanding how these different ways of designing R&D teams affects the extent to which external hires and their collaborators contribute to the firm's innovation performance—a question overlooked by both the literature and many firms—could offer new insights. In search of finding the best R&D team design practices, I provide a more nuanced conceptualization of team knowledge diversity and its consequences for innovation performance. While prior investigations into team diversity have predominantly examined team diversity within a group or team, considering knowledge diversity between multiple teams is integral for maximizing knowledge sharing and production within a firm (Aggarwal et al., 2020; Hansen, 2002; Mortensen and Haas, 2018).

Third, my study also has implications for research on human capital strategy. Scholars have shown inconsistent findings related to whether external hires experience performance gains (Hoisl, 2009; Tartari et al., 2020) or loss (Bidwell, 2011; Campbell et al., 2014; Groysberg et al., 2008; Raffiee and Byun, 2019), often described as the "portability of performance paradox." My findings imply that focusing solely on the performance consequences of external hires to gauge value to firms may be a misspecified paradox. To evaluate whether external hiring is a value creating proposition for the firm, we also need to consider how external hires affect the performance of other employees at the firm. Furthermore, the results on team knowledge diversity suggest that external hires and their teams could experience performance losses due to ineffective team structure. In the worst-case scenario, external hires may leave a firm that does not offer an innovative environment. In fact, a supplementary analysis in Table 2.11 shows that a high level of within-team diversity is associated with longer tenure, while reducing the likelihood of departure within two years. Thus, this paper highlights the importance of jointly considering the ramifications of hiring external talent and efficiently managing them.

[Table 2.11]

Last but not least, my paper contributes to research on knowledge sharing across organizations (Botelho, 2018; Ingram and Roberts, 2000; Kogut and Zander, 1992; Spencer, 2003; von Hippel, 1987). Organization and strategy scholars find that promoting knowledge sharing not only within firms but also across firms, such as among competitors, improves firm outcomes. External hires, who are most likely to come from competitors engaging in similar technology, provide novel ideas that can be exchanged and built upon with new colleagues. In fact, I demonstrate that teammates utilize the new knowledge acquired from the hire and produce inventions with greater technological impact after working with new hires. This study illustrates that for knowledge sharing among team members (within a firm) to become valuable, sourcing different and diverse knowledge from other firms through external hires is critical.

Taken together, these findings have far-reaching implications for managers and employees. Many firms face difficulty evaluating the benefits and costs of external hiring. Specifically, existing research presents mixed evidence related to the performance of external hires at the new firm. Looking beyond the performance implications for focal hires, I explore how hiring affects the performance of other employees at the firm. Working with external hires decreases the productivity of immediate collaborators, but leads them to come up with more novel "breakthrough" innovations. Thus, managers should consider their immediate strategic or performance goals when devising recruiting strategies. For instance, firms trying to produce as many innovation outputs as possible during a short period of time would be better off forming teams with existing employees. Firms focused on creating breakthrough technology in a field should consider bringing in an external hire who can enhance learning. If a recruit has been hired, assigning them to collaborators with greater knowledge distance, rather than those who share a similar knowledge base, could lead to better collaborative performance. Furthermore, designing collaborative teams such that a high level of diversity exists within the team while allowing teams to diverge less from one another can create an environment that fosters innovation performance. Team structures may be affected by firm strategy and/or the team formation decisions employees make in the short-term. However, managers can adjust the composition of teams for better performance. At a minimum, managers could advise employees on how best to create teams with the optimal level of knowledge diversity.

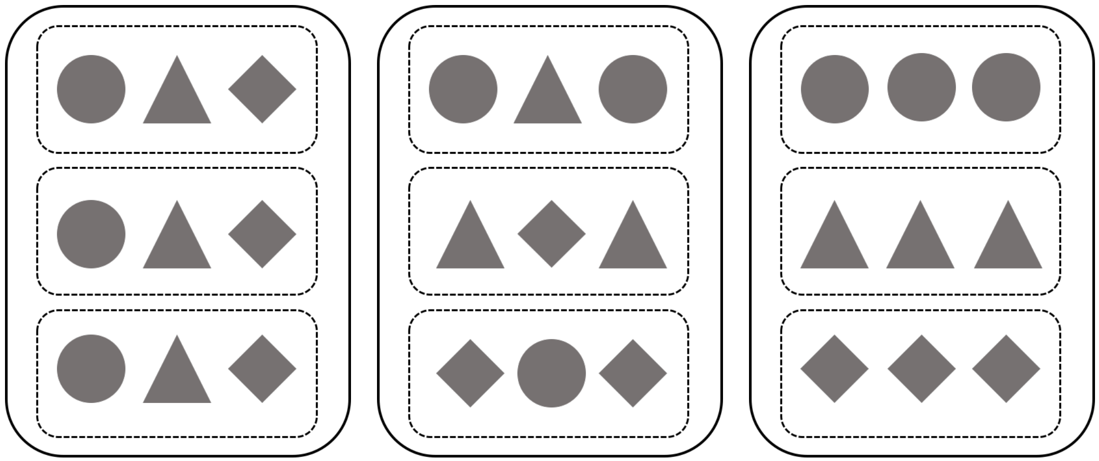
This study also offers insights for employees considering a move to a different firm. In particular, it elucidates what organizational characteristics to look for when job hunting. From an employee's perspective, switching workplaces could bring both benefits (e.g., knowledge spillover) and costs (e.g., adjustment costs). Since post-mobility performance is contingent on team design, evaluating the organizational characteristics of the destination firm is important to ensuring that the new firm allows the inventor to achieve her or his full innovative potential.

Does external hiring constitute a value creating or value destroying proposition for firms? Although the patent data employed in this study offer many benefits, salary information is not included. While I explore how external hiring could bring knowledge benefits to firms, I could not asses whether or not these benefits offset the costs. Yet my results suggest that advantages from hiring accrue both directly from external hires and indirectly from knowledge spillover to their new teammates. The value and success of inventions follow a skewed distribution (Fleming, 2007). Thus, teammates having fewer but more novel and valuable patents may easily counterbalance the productivity loss of and premium wages paid to external hires. The external hiring of star talent may therefore not be an irrational move by firms. Future research could compare how much a recruited inventor contributes to the firm and the associated costs of hiring by collecting compensation information. Nonetheless, this paper highlights how external hires bring knowledge benefits to their teams and how to efficiently design teams to improve the marginal benefits of external hiring. External hiring, which enables knowledge sharing across firms, facilitates more lucrative knowledge sharing among incumbent employees within firms.

Overall, this research tackles two important challenges faced by managers in innovation-driven organizations: how to efficiently manage the talent pool and design teams. Looking beyond the performance implications of new hires, I consider how other members of the firm—teammates of the hires—are impacted by the mobility event. Efficiently designing teams not only improves the innovation performance of external hires but can also enhance the learning benefits for other team members.

2.6 Figures and Tables

Figure 2.1: Within-team Diversity and Across-team Diversity



(a) Firm A
High within-team diversity
Low across-team diversity

(b) Firm B
Intermediate within-team diversity
Intermediate across-team diversity

(c) Firm C
Low within-team diversity
High across-team diversity

Notes: The solid lines represent firm boundaries and dashed lines represent team boundaries. Each inventor possess knowledge in one of the three fields: circle, triangle, and rhombus. If the inventors are assigned to three teams of three, the teams can be organized in at least three different ways. Firm A has high within-team diversity and low across-team diversity. Firm C has low within-team diversity and high across-team diversity. Firm B has an intermediate level of within-team and across-team diversity. Here, the two diversity measures may appear inversely related, since each team has the same number of inventors with the same set of knowledge. Empirically, however, the relationship between the firm-level average within-team and across-team diversity measures is not necessarily dependent or correlated.

Figure 2.2: Distribution of Within-team and Across-team Diversity

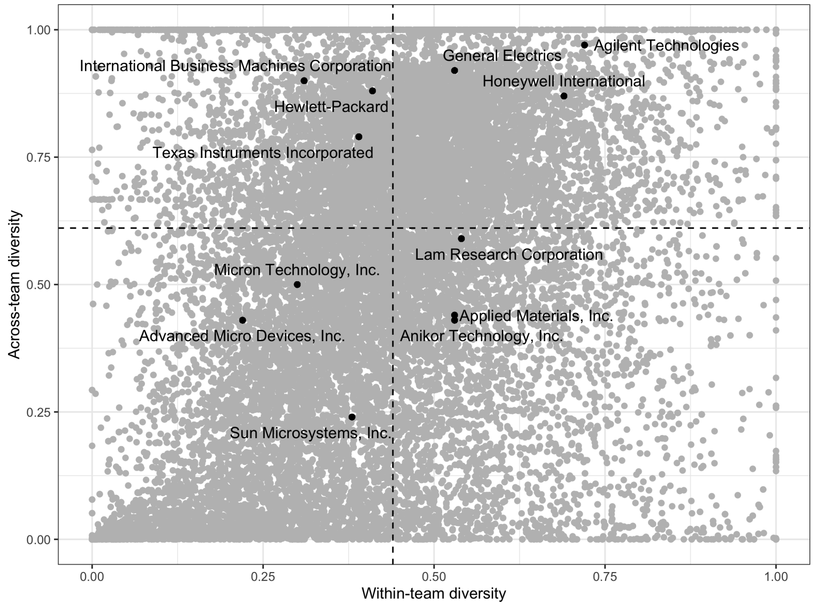


Table 2.1: Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Max
External Hire Characteristics					
Post-mobility Performance					
Number of patents	63,976	3.19	4.84	0.00	160.00
Forward citations	62,417	17.92	39.99	0.00	1,051.00
Top 5% cite	62,417	0.09	0.29	0.00	1.00
Zero cite	62,417	0.19	0.39	0.00	1.00
Number of new tech classes	62,417	1.02	1.34	0.00	20.00
Tech diversity	62,417	0.22	0.28	0.00	0.92
Pre-mobility Characteristics					
Number of patents	63,976	7.62	9.71	1.00	284.00
Forward citations	63,976	31.74	50.59	0.00	1,254.80
Number of tech classes	63,976	3.29	2.51	1.00	77.00
Tech diversity	63,976	0.46	0.28	0.00	0.96
Mobility Characteristics					
Tenure at destination	63,976	3.74	3.05	1.00	34.96
Tenure at departure	63,976	3.47	3.23	1.00	31.80
R&D experience	63,976	7.43	6.17	0.00	36.00
Move window	63,976	659.17	401.29	0.00	1,459.00
Destinatino Firm Characteristics					
Firm-level Average Team Diversity					
Within-team diversity	63,976	0.44	0.16	0.00	1.00
Across-team diversity	63,976	0.62	0.26	0.00	1.00
Destination Firm Characteristics					
Firm age	63,976	31.83	9.54	8.00	42.00
Firm size	63,976	147.65	309.94	0.67	2,253.67
Firm number of inventors	63,976	262.93	553.31	1.00	3,881.00
Firm scope	63,976	21.44	24.46	0.33	129.67
Firm geodiversity	63,976	0.07	0.15	0.00	0.85
Firm growth rate	63,976	0.38	0.52	0.00	6.07
Firm team size	63,976	2.84	0.91	1.12	13.71
Non-Mover Characteristics					
Post-mobility Performance					
Number of patents	23,069	1.21	2.79	0.00	80.00
Forward citations	11,060	13.23	30.25	0.00	760.00
Top 5% cite	11,060	0.08	0.28	0.00	1.00
Zero cite	11,060	0.19	0.39	0.00	1.00
Number of new tech classes	11,060	0.82	1.06	0.00	15.00
Tech diversity	11,060	0.19	0.27	0.00	0.89
Pre-mobility Performance					
Number of patents	23,069	4.54	7.20	0.00	252.00
Forward citations	23,069	24.12	44.48	0.00	1,048.67
Number of unique tech classes	23,069	1.62	1.97	0.00	23.00
Tech diversity	23,069	0.38	0.30	0.00	0.93

Notes: The external hire sample is based on the complete case sample used for Model 1 in Table 2.7. The pre-mobility and post-mobility performances of external hires and non-movers are captured throughout their tenure at the destination or departure firm.

Table 2.1: Descriptive Statistics (continued)

Statistic	N	Mean	St. Dev.	Min	Max
Teammate Characteristics					
Knowledge distance	26,816	0.50	0.36	0.00	1.00
Tenure (pre-mobility)	38,254	4.55	5.32	0.00	34.26
Tenure (post-mobility)	38,254	5.67	4.49	0.00	35.00
R&D experience	38,254	11.16	7.54	0.00	36.55
Post-mobility Performance					
Number of patents	38,254	3.48	9.71	0.00	465.00
Forward citations	19,256	22.57	43.98	0.00	906.00
Number of new tech classes	19,256	1.54	1.67	0.00	37.00
Tech diversity	19,256	0.40	0.29	0.00	0.95
Top 5% cite	19,256	0.23	0.42	0.00	1.00
Zero cite	19,256	0.53	0.50	0.00	1.00
Pre-mobility Performance					
Number of patents	38,254	2.84	8.59	0.00	363.00
Forward citations	16,845	29.63	55.43	0.00	828.00
Number of tech classes	16,845	2.83	2.91	1.00	86.00
Tech diversity	16,845	0.39	0.30	0.00	0.95
Non-Teammate Characteristics					
Knowledge distance	20,557	0.76	0.32	0.00	1.00
Tenure (pre-mobility)	31,056	5.70	6.14	0.00	36.19
Tenure (post-mobility)	31,056	5.69	4.61	0.00	35.87
R&D experience	31,056	12.20	7.78	0.00	36.45
Post-mobility Performance					
Number of patents	31,056	6.73	13.18	0.00	532.00
Forward citations	31,049	19.21	37.35	0.00	808.83
Number of new tech classes	31,049	1.55	1.75	0.00	40.00
Tech diversity	31,049	0.39	0.29	0.00	0.96
Top 5% cite	31,049	0.20	0.40	0.00	1.00
Zero cite	31,049	0.51	0.50	0.00	1.00
Pre-mobility Performance					
Number of patents	31,056	5.43	11.53	0.00	475.00
Forward citations	26,208	25.00	47.09	0.00	1,110.00
Number of tech classes	26,208	2.79	2.94	1.00	95.00
Tech diversity	26,208	0.37	0.30	0.00	0.97

Notes: The pre-mobility and post-mobility performances of teammembers and non-teammembers are captured using 2-year window before and after the mobility event.

Table 2.2: Pairwise Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) No. of patents												
(2) Forward citations	0.02											
(3) Top 5% cite	0.26	0.43										
(4) Zero cite	-0.16	-0.18	-0.14									
(5) No. of new tech classes	0.65	0.03	0.20	-0.15								
(6) Tech diversity	0.50	-0.01	0.17	-0.22	0.66							
(7) Within-team diversity	0.00	0.00	0.00	-0.02	0.09	0.05						
(8) Across-team diversity	0.01	-0.05	-0.05	-0.05	0.09	0.05	0.39					
(9) Tenure at destination	0.52	0.01	0.14	-0.15	0.49	0.44	0.03	0.08				
(10) Tenure at departure	0.02	-0.02	-0.01	-0.01	0.00	0.01	0.04	0.02	0.02			
(11) R&D xperinece	-0.01	-0.05	-0.01	0.03	-0.09	0.00	0.03	-0.01	-0.10	0.44		
(12) Move window	-0.05	-0.02	-0.04	0.03	0.05	-0.07	0.02	0.06	0.13	-0.01	-0.14	
(13) Firm age	0.03	0.07	-0.01	-0.09	0.08	0.03	0.03	0.29	0.11	-0.06	-0.06	0.04
(14) Firm size	0.04	-0.06	-0.02	0.03	0.06	0.06	0.07	0.25	-0.02	-0.04	-0.02	0.01
(15) Firm no. of inventors	0.03	-0.06	-0.02	0.04	0.04	0.04	0.08	0.25	-0.03	-0.04	-0.01	0.01
(16) Firm scope	0.08	-0.04	-0.02	-0.04	0.15	0.12	0.16	0.47	0.07	-0.02	-0.02	0.04
(17) Firm geodiversity	-0.01	0.02	0.00	0.00	-0.01	-0.01	-0.04	0.03	0.01	-0.01	-0.01	0.02
(18) Firm growth rate	0.08	0.04	0.02	-0.07	0.08	0.10	0.05	0.01	0.11	0.12	-0.05	-0.01
(19) Firm team size	-0.06	-0.06	0.01	0.15	-0.10	-0.06	-0.11	-0.28	-0.14	0.01	0.08	-0.07
(20) No. of patents (pre-mobility)	0.04	-0.05	0.01	0.02	-0.11	0.04	-0.01	-0.04	-0.1	0.14	0.52	-0.16
(21) Forward citations (pre-mobility)	0.02	0.37	0.16	-0.03	0.00	0.01	-0.02	-0.08	0.01	-0.04	-0.01	-0.01
(22) No. of tech classes (pre-mobility)	0.02	-0.06	0.00	0.03	-0.09	0.06	0.06	0.02	-0.11	0.16	0.60	-0.17
(23) Tech diversity (pre-mobility)	0.00	-0.06	0.00	0.04	-0.08	0.06	0.08	0.02	-0.12	0.20	0.49	-0.23

Table 2.2: Pairwise Correlations (continued)

	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
(1) No. of patents											
(2) Forward citations											
(3) Top 5% cite											
(4) Zero cite											
(5) No. of new tech classes											
(6) Tech diversity											
(7) Within-team diversity											
(8) Across-team diversity											
(9) Tenure at destination											
(10) Tenure at departure											
(11) R&D experience											
(12) Move window											
(12) Firm age											
(14) Firm size	0.09										
(15) Firm no. of inventors	0.11	0.97									
(16) Firm scope	0.25	0.74	0.71								
(17) Firm geodiversity	0.05	-0.09	-0.10	-0.07							
(18) Firm growth rate	-0.39	-0.09	-0.10	-0.06	-0.04						
(19) Firm team size	-0.17	0.02	0.07	-0.11	-0.05	-0.05					
(20) No. of patents (pre-mobility)	-0.07	0.01	0.02	-0.02	-0.02	-0.04	0.08				
(21) Forward citations (pre-mobility)	-0.04	-0.01	-0.02	-0.03	0.02	0.04	-0.01	0.00			
(22) No. of tech classes (pre-mobility)	-0.05	0.04	0.04	0.02	-0.03	-0.06	0.06	0.74	-0.03		
(23) Tech diversity (pre-mobility)	-0.05	0.04	0.05	0.03	-0.03	-0.06	0.06	0.39	-0.05	0.73	

Table 2.3: Team Design Characteristics by Firms

(a) Team Knowledge Diversity by Firm Characteristics

	Within-team Diversity	Across-team Diversity	Average Inventor Tenure
Firm Size			
Small	0.43 ± 0.22	0.48 ± 0.32	6.89 ± 3.28
Medium	0.43 ± 0.14	0.63 ± 0.23	6.69 ± 2.64
Large	0.45 ± 0.09	0.73 ± 0.17	6.60 ± 2.16
Firm Average Team Size			
Small	0.45 ± 0.17	0.67 ± 0.27	5.80 ± 2.77
Medium	0.44 ± 0.15	0.63 ± 0.24	6.82 ± 2.50
Large	0.42 ± 0.16	0.54 ± 0.28	7.56 ± 2.64
Patent Growth Rate			
Low	0.44 ± 0.15	0.66 ± 0.25	7.81 ± 2.61
Medium	0.42 ± 0.16	0.59 ± 0.26	6.36 ± 2.70
High	0.45 ± 0.16	0.61 ± 0.27	6.00 ± 2.56

(b) Knowledge Diversity by Team Compositions

	Average Inventor Tenure	Average Team Size
Within-team Diversity		
High	6.70 ± 2.58	2.74 ± 0.73
Low	6.75 ± 2.87	2.93 ± 1.04
Across-team diversity		
High	6.37 ± 2.41	2.63 ± 0.61
Low	7.10 ± 2.99	3.05 ± 1.09

Notes: The statistics in (a) show the mean and standard deviation of within-team diversity, across-team diversity, and average inventure tenure values in each group. The tercile cut-off points for firm size, are (0.67, 14.67, 74.67, 2,253.67); for average team size are (1.13, 2.41, 3.00, 13.71); and for patent growth rate (3-year CAGR) are (0.00, 0.09, 0.32, 6.07). The statistics in (b) show the mean and standard deviation for firms with high or low within-team and across-team diversity values. The cut-off points are determined using the median values of within-team diversity and across-team measures, 0.44 and 0.68.

Table 2.4: External Hires' Post-mobility Innovation Performance

Dependent variable:	No. of patents	Forward citations	Top 5% cite	Zero cite	No.of new tech classes	Tech diversity
Model specification:	*Poisson (link = log)*	*OLS (log-log)*	*OLS*	*OLS*	*Poisson (link = log)*	*OLS*
	(1)	(2)	(3)	(4)	(5)	(6)
External Hire	0.655	0.211	−0.011	0.029	0.180	0.017
	(0.022)	(0.100)	(0.004)	(0.007)	(0.023)	(0.004)
No. of patents	0.319					
(pre-mobility)	(0.010)					
Forward citations		0.129	0.001	−0.000		
(pre-mobility)		(0.013)	(0.000)	(0.000)		
No. of tech classes					−0.123	
(pre-mobility)					(0.017)	
Tech diversity						0.120
(pre-mobility)						(0.006)
Tenure	−0.032	−0.198	−0.001	0.002	0.051	−0.002
at departure	(0.013)	(0.065)	(0.000)	(0.001)	(0.013)	(0.001)
Tenure	0.988	0.533	0.013	−0.011	0.632	0.041
at destination	(0.017)	(0.070)	(0.001)	(0.001)	(0.015)	(0.001)
Move window	−0.041	−0.132	−0.000	0.000	−0.027	−0.000
	(0.007)	(0.033)	(0.000)	(0.000)	(0.006)	(0.000)
R&D experience	−0.125	0.190	0.000	−0.002	−0.071	0.000
	(0.015)	(0.057)	(0.000)	(0.000)	(0.016)	(0.000)
Firm age	−0.112	0.086	−0.001	−0.000	0.052	−0.001
	(0.036)	(0.226)	(0.000)	(0.001)	(0.043)	(0.000)
Firm size	0.533	1.392	0.000	−0.000	0.289	0.000
	(0.036)	(0.167)	(0.000)	(0.000)	(0.035)	(0.000)
Firm no. of	−0.378	−1.543	−0.000	0.000	−0.279	−0.000
inventors	(0.043)	(0.246)	(0.000)	(0.000)	(0.045)	(0.000)
Firm scope	−0.126	0.230	−0.000	−0.000	0.060	0.001
	(0.028)	(0.185)	(0.000)	(0.000)	(0.037)	(0.000)
Firm geodiversity	−0.003	−0.015	−0.032	0.047	−0.002	−0.018
	(0.002)	(0.011)	(0.015)	(0.030)	(0.002)	(0.012)
Firm growth rate	0.002	−0.087	−0.005	0.005	0.014	0.004
	(0.010)	(0.049)	(0.004)	(0.007)	(0.010)	(0.005)
Firm team size	0.227	1.126	0.006	−0.006	0.134	0.004
	(0.053)	(0.223)	(0.003)	(0.004)	(0.049)	(0.003)
Constant	−0.092	−0.215	0.119	0.143	−1.009	0.203
	(0.333)	(1.397)	(0.067)	(0.071)	(0.384)	(0.077)
Observations	46,138	33,438	33,438	33,438	33,438	33,438
R^2		0.172	0.041	0.129		0.180

Notes: *External Hire* is a binary variable that takes a value of 1 if the mobility cases are for external hires (0 if non-movers), respectively. The controls are included as logged values for the models on number of patents (1), forward citations (2), and number of technological classes (5). All models include technology class and move year fixed effects. Robust standard errors, clustered at the destination firm level, in parentheses.

Table 2.5: Teammates' (vs. Non-teammates') Post-mobility Innovation Performance

Dependent variable:	No. of patents	Forward citations	Top 5% cite	Zero cite	No.of new tech classes	Tech diversity
Model specification:	*Poisson (link = log)*	*OLS (log-log)*	*OLS*	*OLS*	*Poisson (link = log)*	*OLS*
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Short-term (2-year) performance before controlling for prior performance						
Teammate	−0.585	0.213	0.036	0.018	0.021	0.014
	(0.014)	(0.039)	(0.004)	(0.004)	(0.010)	(0.003)
Constant	1.568	1.362	0.200	0.378	0.009	0.347
	(0.310)	(0.777)	(0.074)	(0.080)	(0.201)	(0.052)
Observations	62,112	46,816	46,816	46,816	46,816	46,816
R^2		0.133	0.043	0.258		0.090
Panel B: Short-term (2-year) performance after controlling for prior performance						
Teammate	−0.052	0.116	0.024	0.015	0.007	0.003
	(0.011)	(0.039)	(0.004)	(0.005)	(0.010)	(0.003)
Constant	1.173	0.996	0.191	0.350	−0.344	0.436
	(0.244)	(0.750)	(0.077)	(0.082)	(0.199)	(0.050)
Observations	62,112	39,892	39,892	39,892	39,892	39,892
R^2		0.171	0.100	0.263		0.180
Panel C: 3-year performance after controlling for prior performance						
Teammate	0.029	0.102	0.031	−0.006	0.015	0.006
	(0.014)	(0.033)	(0.004)	(0.002)	(0.010)	(0.003)
Constant	1.214	1.225	0.202	−0.004	−0.384	0.476
	(0.325)	(0.654)	(0.080)	(0.039)	(0.197)	(0.048)
Observations	62,112	42,634	42,671	42,671	42,634	42,634
R^2		0.191	0.106	0.032		0.199
Panel D: Long-term (throughout tenure) performance after controlling for prior performance						
Teammate	0.049	0.249	0.092	0.058	0.177	−0.029
	(0.018)	(0.035)	(0.005)	(0.005)	(0.014)	(0.003)
Constant	1.935	2.136	0.299	0.615	−0.774	0.342
	(0.417)	(0.696)	(0.096)	(0.090)	(0.262)	(0.057)
Observations	62,112	36,385	36,385	35,945	36,678	36,385
R^2		0.199	0.110	0.201		0.179

Notes: *Teammate* is a binary variable that takes a value of 1 if the mobility cases are for teammates (0 if non-teammates). Unreported control variables include R&D experience, tenure at the time of the mobility case, and firm characteristics used in Table 2.4 (firm age, size, number of inventors, scope, geodiversity, growth rate, and average team size). The controls are included as logged values in models regarding number of patents (1), forward citations (2), and number of technological classes (5). All models include technology class and move year fixed effects. Robust standard errors, clustered at the destination firm level, in parentheses.

Table 2.6: New Knowledge Transferred from External Hires to Teammates

Dependent variable:	No. of new tech classes	No. of new tech classes learned from the focal inventor		
Model Specification:	*Poisson (link = log)*			
	(1)	(2)	(3)	(4)
Teammate	0.007	0.192	0.399	0.512
	(0.010)	(0.028)	(0.062)	(0.039)
Within-team diversity			0.156	
			(0.038)	
Within-team diversity × Teammate			0.228	
			(0.062)	
Knowledge distance				0.071
				(0.019)
Knowledge distance × Teammate				0.378
				(0.033)
Constant	−0.344	−2.302	−2.001	−1.869
	(0.199)	(0.624)	(0.636)	(0.754)
Observations	39,892	39,892	39,892	30,370

Notes: Model 1 in this table is equivalent to model 5 in Table 2.5 Panel B. All models include control variables from model 5 in Table 2.5, technology class and move year fixed effects. Robust standard errors, clustered at the destination firm level, in parentheses.

Table 2.7: Technological Diversity and Post-mobility Innovation Performance

Dependent variable:	No. of patents	Forward citations	Top 5% cite	Zero cite	No.of new tech classes	Tech diversity
Model specification:	*Poisson (link = log)*	*OLS (log-log)*	*OLS*	*OLS*	*Poisson (link = log)*	*OLS*
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Team knowledge diversity and the performance of external hires (throughout tenure)						
Within-team diversity	0.012	0.024	0.021	0.006	0.069	0.045
	(0.013)	(0.033)	(0.011)	(0.013)	(0.015)	(0.009)
Across-team diversity	−0.015	−0.072	−0.055	0.048	−0.014	−0.035
	(0.005)	(0.024)	(0.008)	(0.011)	(0.005)	(0.007)
Constant	−0.478	2.251	0.108	0.038	−1.680	0.044
	(0.200)	(0.957)	(0.041)	(0.040)	(0.243)	(0.038)
Observations	63,976	62,417	62,417	62,417	62,417	62,417
R^2		0.196	0.057	0.156		0.250
Panel B: Team knowledge diversity and the short-term (2-year) performance of teammates						
Within-team diversity	0.028	0.045	0.024	−0.072	0.101	0.092
	(0.018)	(0.060)	(0.032)	(0.034)	(0.026)	(0.020)
Across-team diversity	−0.027	−0.044	−0.086	−0.052	−0.016	−0.055
	(0.010)	(0.027)	(0.023)	(0.023)	(0.008)	(0.014)
Constant	1.994	3.224	0.311	0.526	0.266	0.263
	(0.459)	(0.750)	(0.131)	(0.140)	(0.362)	(0.113)
Observations	31,056	13,688	13,688	13,757	13,688	13,688
R^2		0.187	0.102	0.274		0.218
Panel C: Team knowledge diversity and the long-term (throughout tenure) performance of teammates						
Within-team diversity	0.030	0.035	−0.007	−0.059	0.086	0.064
	(0.021)	(0.047)	(0.034)	(0.031)	(0.028)	(0.020)
Across-team diversity	−0.020	0.013	−0.086	−0.046	−0.016	−0.083
	(0.013)	(0.037)	(0.024)	(0.022)	(0.012)	(0.015)
Constant	−0.324	2.689	0.126	0.345	−1.071	0.020
	(0.626)	(0.644)	(0.145)	(0.171)	(0.435)	(0.119)
Observations	31,056	11,979	11,979	11,979	11,979	11,979
R^2		0.239	0.255	0.373		0.201

Notes: The team diversity measures and controls are included as logged values for the models on number of patents (1), forward citations (2), and number of technological classes (5). Unreported control variables include R&D experience, tenure at the time of the mobility case, and firm characteristics used in Table 2.4 (firm age, size, number of inventors, scope, geodiversity, growth rate, and average team size). All models include technology class and move year fixed effects. Robust standard errors, clustered at the destination firm level, in parentheses.

Table 2.8: Knowledge Distance and Post-mobility Innovation Performance

Dependent variable:	No. of patents	Forward citations	Top 5% cite	Zero cite	No.of new tech classes	Tech diversity
Model specification:	*Poisson (link = log)*	*OLS (log-log)*	*OLS*	*OLS*	*Poisson (link = log)*	*OLS*
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Knowledge distance and the performance of external hires (throughout tenure)						
Knowledge distance	0.014	0.011	0.036	0.019	0.100	0.039
	(0.004)	(0.018)	(0.007)	(0.007)	(0.007)	(0.005)
Constant	−0.320	3.463	0.200	−0.007	−1.550	0.104
	(0.248)	(1.277)	(0.124)	(0.052)	(0.344)	(0.092)
Observations	21,819	21,545	21,545	21,545	21,545	21,545
R^2		0.185	0.068	0.112		0.244
Panel B: Knowledge distance and the short-term (2-year) performance of teammates						
Knowledge distance	0.043	0.087	0.070	0.043	0.105	0.101
	(0.005)	(0.014)	(0.011)	(0.011)	(0.006)	(0.006)
Constant	2.257	3.942	0.296	0.393	0.615	0.229
	(0.388)	(1.244)	(0.140)	(0.143)	(0.330)	(0.085)
Observations	21,819	13,201	13,201	13,268	13,201	13,201
R^2		0.188	0.103	0.274		0.228
Panel C: Knowledge distance and the long-term (throughout tenure) performance of teammates						
Knowledge distance	0.028	0.044	0.040	0.014	0.088	0.055
	(0.009)	(0.021)	(0.013)	(0.012)	(0.009)	(0.008)
Constant	−0.150	2.938	0.111	0.219	−0.873	−0.024
	(0.683)	(0.645)	(0.146)	(0.162)	(0.519)	(0.128)
Observations	21,819	11,553	11,553	11,553	11,553	11,553
R^2		0.243	0.255	0.372		0.202

Notes: The knowledge distance measure and controls are included as logged values in models regarding number of patents (1), forward citations (2), and number of technological classes (5). Unreported control variables include R&D experience, tenure at the time of the mobility case, and firm characteristics used in Table 2.4 (firm age, size, number of inventors, scope, geodiversity, growth rate, and average team size). All models include technology class and move year fixed effects. Robust standard errors, clustered at the destination firm level, in parentheses.

Table 2.9: Pre-mobility Characteristics and Technological Diversity

Dependent variable:	Within-team diversity	Across-team diversity
Model specification:	*OLS*	
	(1)	(2)
No. of patents	−0.078	−0.062
(pre-mobility)	(0.006)	(0.006)
Forward citations	−0.004	−0.064
(pre-mobility)	(0.005)	(0.005)
No. of tech classes	0.085	0.078
(pre-mobility)	(0.008)	(0.009)
Tech diversity	0.027	0.003
(pre-mobility)	(0.006)	(0.006)
Constant	−0.545	0.380
	(0.116)	(0.101)
Observations	72,219	66,945
R^2	0.053	0.106

Notes: All variables are standardized to have a mean of zero and a standard deviation of one. All models include move year and industry fixed effects. Robust standard errors, clustered at the destination firm level, in parentheses.

Table 2.10: Mobility, Technological Diversity and Post-mobility Innovation Performance

Dependent variable:	No. of patents	Forward citations	Top 5% cite	Zero cite	No.of new tech classes	Tech diversity
Model specification:	*Poisson (link = log)*	*OLS (log-log)*	*OLS*	*OLS*	*Poisson (link = log)*	*OLS*
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: The effect of diversity among both "mover" and "non-mover" populations						
Within-team diversity	0.022	0.032	0.029	0.036	0.114	0.044
	(0.014)	(0.061)	(0.014)	(0.022)	(0.030)	(0.014)
Across-team diversity	−0.028	−0.162	−0.044	0.065	−0.013	−0.049
	(0.007)	(0.042)	(0.010)	(0.018)	(0.008)	(0.009)
External Hire	0.654	0.204	−0.011	0.028	0.188	0.017
	(0.022)	(0.100)	(0.004)	(0.007)	(0.022)	(0.004)
Constant	−0.095	−0.592	0.130	0.109	−0.813	0.212
	(0.335)	(1.414)	(0.068)	(0.072)	(0.395)	(0.076)
Observations	45,688	33,287	33,287	33,287	33,287	33,287
R^2		0.173	0.042	0.130		0.181
Panel B: The effect of diversity for "mover" relative to "non-mover" population						
Within-team diversity	−0.016	0.018	0.037	0.046	0.073	0.052
	(0.044)	(0.170)	(0.039)	(0.048)	(0.085)	(0.032)
Across-team diversity	−0.041	−0.436	−0.051	0.115	−0.034	−0.084
	(0.031)	(0.140)	(0.024)	(0.031)	(0.043)	(0.018)
External Hire	0.705	0.395	−0.013	0.074	0.242	−0.008
	(0.039)	(0.170)	(0.014)	(0.025)	(0.066)	(0.014)
Within-team diversity ×	0.049	0.041	−0.008	−0.015	0.053	−0.008
External Hire	(0.045)	(0.182)	(0.041)	(0.054)	(0.088)	(0.035)
Across-team diversity ×	0.013	0.289	0.008	−0.060	0.020	0.043
External Hire	(0.032)	(0.140)	(0.026)	(0.033)	(0.043)	(0.020)
Constant	−0.148	−0.878	0.132	0.075	−0.873	0.231
	(0.335)	(1.424)	(0.068)	(0.074)	(0.397)	(0.076)
Observations	45,688	33,287	33,287	33,287	33,287	33,287
R^2		0.173	0.042	0.130		0.181

Notes: *External Hire* is a binary variables taking the value of 1 if the observations are for external hires (0 if non-movers). All models include control variables from Table 2.7, move year. and industry fixed effects. The team diversity measures and controls are included as logged values in models regarding number of patents (1), forward citations (2), and number of technological classes (5). Robust standard errors, clustered at the destination firm level, in parentheses.

Table 2.11: Team Diversity and External Hire Retention

Dependent variable:	Likelihood of departure within two years	Tenure at destination firm
Model specification:	*OLS*	
	(1)	(2)
Within-team diversity	−0.036	0.251
	(0.016)	(0.142)
Across-team diversity	0.018	−0.100
	(0.012)	(0.109)
Constant	0.381	5.593
	(0.095)	(0.856)
Observations	63,976	63,976
R^2	0.098	0.129

Notes: All models include control variables, move year and industry fixed effects. Robust standard errors, clustered at the destination firm level, in parentheses.

2.7 Appendix of Chapter 2

Here I describe in detail how the two knowledge diversity measures are calculated. I list the notations used to describe how *within-team diversity* and *across-team diversity* are computed: inventor mobility event m, inventor i, firm f, patent p, and patent (main) class k.

Within-team Diversity

For each inventor mobility case, m, I derive a list of patents, P_m, applied by the firm in the move year. For each of the patents $p \in P_m$ in the list, I generate a list of inventors, I_p. For each inventor $i \in I_p$, I define the vector $InvClassExp_i$ as the total technological knowledge experience gained throughout her or his career before joining the destination firm. The vector $InvClassExp_i$ contains the count of the inventor's patents in all primary patent classes k. To calculate the diversity between two inventors, i and $-i$, I measure the cosine similarity score, $Cos(i, -i)$, between two vectors, $InvClassExp_i$ and $InvClassExp_{-i}$ (Adams, 1990; Aggarwal et al., 2020; Jaffe, 1986):

$$Cos(i, -i) = \frac{InvClassExp_i \cdot InvClassExp_{-i}}{||InvClassExp_i|| \times ||InvClassExp_{-i}||}.$$

Since cosine similarity is a similarity measure, I subtract the similarity value from 1 to obtain a diversity value. The diversity measure ranges from 0 to 1, with 1 indicating a completely diverse group with no technological overlap and 0 representing a homogeneous group with full overlap. For a given team of inventors $i \in I_p$ on a patent team p, I form all possible dyads between the teams of inventors at firm f. I calculate the average inventor pair's diversity score for each team. Then, I take the average across all patents P_m. The within-team diversity score of the destination firm for each mobility case m is defined as:

$$Within_m = \frac{1}{N}\sum_{n=1}^{N}\frac{\sum_{i,-i} 1 - Cos(i,-i)}{\sum_{i,-i}},\ \forall p \in P_m,\ i \in I_p \mid i < -i,$$

where N denotes the number of patent teams $p \in P_m$.

Across-team Diversity

Instead of directly using a class experience vector for each individual, I create a vector for each team, $TeamClassExp_p$. The class experience vector for each patent team, $TeamClassExp_p$, is the sum of the class experience vectors of inventors i on a patent team p:

$$TeamClassExp_p = \sum_{i \in I_p} InvClassExp_i.$$

Then, I use $Cos(p,-p)$ calculation to measure the pairwise diversity between two patent teams, p and $-p$:

$$Cos(p,-p) = \frac{TeamClassExp_p \cdot TeamClassExp_{-p}}{||TeamClassExp_p|| \times ||TeamClassExp_{-p}||}.$$

For each mobility case m, I gather a list of patent teams P_m by the destination firm in the move year. The across-team diversity at the destination firm for each mobility case m is defined as:

$$Across_m = \frac{1}{N}\sum_{n=1}^{N} 1 - Cos(p,-p),\ \forall p \in P_m \mid p < -p.$$

Illustrative Example

I show the calculations for the two diversity measures for Firm B in Figure 2.1b. The $InvClassExp_i$ for the members in three teams and the cosine similarity matrix for each team would be:

$$\begin{array}{cc} p_1 & \begin{array}{ccc} i_1 & i_2 & i_3 \end{array} \\ \begin{array}{c} k_{circle} \\ k_{triangle} \end{array} & \begin{pmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \end{pmatrix} \end{array} \quad \begin{array}{cc} p_2 & \begin{array}{ccc} i_1 & i_2 & i_3 \end{array} \\ \begin{array}{c} k_{triangle} \\ k_{rhombus} \end{array} & \begin{pmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \end{pmatrix} \end{array} \quad \begin{array}{cc} p_3 & \begin{array}{ccc} i_1 & i_2 & i_3 \end{array} \\ \begin{array}{c} k_{rhombus} \\ k_{circle} \end{array} & \begin{pmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \end{pmatrix} \end{array} \text{ and}$$

$$\begin{array}{cc} & \begin{array}{ccc} i_1 & i_2 & i_3 \end{array} \\ \begin{array}{c} i_1 \\ i_2 \\ i_3 \end{array} & \begin{pmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{pmatrix} \end{array}.$$

Using equation 2.7, I get a within-team diversity value of $\frac{1}{3}((1-0)+(1-1)+(1-0)) = 0.67$ for each team, leading to the average value of 0.67 for Firm B. For across-team diversity measure, I calculate the $TeamClassExp_p$ and then the cosine similarity score between each pair of patent teams $(p, -p)$:

$$\begin{array}{cc} & \begin{array}{ccc} p_1 & p_2 & p_3 \end{array} \\ \begin{array}{c} k_{circle} \\ k_{triangle} \\ k_{rhombus} \end{array} & \begin{pmatrix} 2 & 0 & 1 \\ 1 & 2 & 0 \\ 0 & 1 & 2 \end{pmatrix} \end{array} \text{ and } \begin{array}{cc} & \begin{array}{ccc} p_1 & p_2 & p_3 \end{array} \\ \begin{array}{c} p_1 \\ p_2 \\ p_3 \end{array} & \begin{pmatrix} 1.0 & 0.4 & 0.4 \\ 0.4 & 1.0 & 0.4 \\ 0.4 & 0.4 & 1.0 \end{pmatrix} \end{array}.$$

The across-team diversity for Firm B equals $\frac{1}{3}((1-0.4)+(1-0.4)+(1-0.4)) = 0.6$.

Knowledge diversity Measures in Practice

To assist interpretation of the results in Table 2.7, I demonstrate what a one standard deviation change in within-team diversity and across-team diversity would look like in practice. Returning to the stylized example I provide in Figure 2.1b (Firm B), I illustrate two scenarios: (1) an external hire with "star" technology and (2) an external hire with "circle" technology joining Firm B and becoming a member of the first team (with two "circle" members and one "triangle" member). I then describe how each scenario shifts the two team diversity measures. Before the new hire joins Firm B, the within-team diversity for each team is 0.67 and the firm's across-team diversity value is 0.60. Although this is a simplified example that assumes three teams and nine inventors in a firm, the figure roughly mirrors the average team composition characteristics in my sample: the average team size is 2.8 and each team has 3.6 unique technological knowledge area (main patent class).

In the first scenario, if the hire with “star” technology—a new technology that did not exist at the firm—joins the first team, the team’s within-team diversity value increases from 0.67 to 0.83. The firm’s within-team diversity value, taking the average of the three team-level diversity values, would change from 0.67 to $\frac{1}{3}(0.83+0.67+0.67) = 0.72$. In the second scenario, if the hire with “circle” technology—knowledge that already exists in the team—joins the team, the team’s within-team diversity value decreases from 0.67 to 0.50 and the firm’s within-team diversity value would decrease to $\frac{1}{3}(0.50 + 0.67 + 0.67) = 0.61$. Thus, bringing a new member who possesses new technology, relative to having a member with existing technology, could shift the team’s within-team diversity value by 0.33, about two standard deviations, and the firm’s average within-team diversity value by 0.11, roughly 70 percent of one standard deviation.

For across-team diversity, the value in the first scenario increases from 0.60 to $\frac{1}{3}(0.63 + 0.63 + 0.60) = 0.62$. In the second scenario, across-team diversity increases to $\frac{1}{3}(0.72+0.58+0.60) = 0.63$. The difference in across-team diversity of 0.01 accounts for three percent of one standard deviation. Across-team diversity is less sensitive to the addition of a new hire, because an individual’s knowledge diversity contribution is diluted when deriving the team’s sum of patenting experience in different technological classes. Across-team diversity is a more macro-level construct that could be more difficult to control for than within-team diversity, yet it has a significant impact on inventor knowledge production at firms and can be regulated by managers restructuring teams.

Chapter 3

The Evaluation of Founder Failure and Success by Hiring Firms: A Field Experiment

3.1 Introduction

The mobility of individuals across organizations provides insights into the structures and processes within these organizations. Research on the organizational spawning of entrepreneurs, or the *outflow* of employees from established firms to entrepreneurial ventures, has helped demonstrate that some firms are better than others at incubating future innovation-driven ventures (e.g., high-tech and STEM ventures) (Chatterji, 2009; Elfenbein et al., 2010; Feldman et al., 2019; Phillips, 2002; Sørensen and Fassiotto, 2011; Sørensen, 2007). For example, former employees from smaller and younger firms, which are arguably richer in entrepreneurial resources, are better positioned to launch successful ventures (Gompers et al., 2005; Sørensen, 2007; Sørensen and Stuart, 2000; Xu and Ruef, 2004). Examining the reverse process, or the *inflow* of former entrepreneurs (or founders) into established firms has received considerably less attention, yet offers a similar opportunity to understand other organizational processes, such as how firms evaluate entrepreneurial human capital. This view provides insight into a firm's human capital strategy, which reflects its resources, practices, and structures (Baron, 2004; Bidwell, 2011; Chadwick and Dabu, 2009; Molloy and Barney, 2015).

Research on the wage implications of entrepreneurship, as well as organizational research on hiring more generally, lead to unclear expectations. Former founders can be argued to be advantaged in the labor market because their entrepreneurial experience sends a strong, positive quality signal such as possessing greater capabilities and human capital (Agarwal et al., 2004; Burton and Beckman, 2007; Campbell, 2013; Gompers et al., 2005). Conversely, some scholars argue that entrepreneurial experience conveys an ambiguous quality signal, making it challenging for hiring firms to assess the quality of former founders relative to potential employees without entrepreneurial experience (Anton and Yao, 1995; Hegde and Tumlinson, 2021; Mahieu et al., 2019; Sorenson et al., 2020). Further, organizational scholars have shown that a priority for hiring firms is a job candidate's ability to fit into and remain committed to their firm (Chatman, 1991; Galperin et al., 2019; Goldberg et al., 2016; Leung, 2014; O'Reilly III et al., 1991; Rivera, 2012), which may also disadvantage former founders relative to wage employees. Therefore, to better understand how founder experience is evaluated in the labor market it is necessary to disentangle these two organizational perspectives: (i) mechanisms related to information asymmetry about quality (capabilities, human capital) and (ii) mechanisms related to concerns about fit and commitment.

To uncover the mechanisms driving how founder experience affects subsequent labor market outcomes, we consider how the evaluations of prior founders vary based on their venture's outcome: success versus failure. Successful founders would arguably send a stronger signal of their quality than would failed founders, because entrepreneurial success is rare and may require exceptional capabilities. Thus, if information asymmetry about quality is the driving mechanism in the evaluation of former founders, we would expect hiring firms to favor successful founders over failed founders. According to research on entrepreneurship and information asymmetry, employees leave their firms when they possess superior capabilities which they cannot signal to wage employers resulting in them leaving to launch their own ventures (Anton and Yao, 1995; Hegde and Tumlinson, 2021). Under conditions of complete information, hiring firms would seek to capture former founders, and in particular successful founders, who are more likely to have superior capability and entrepreneurial human capital (Campbell, 2013; Lazear, 2005; Luzzi and Sasson, 2016). This pattern would indicate that organizations primarily view entrepreneurial human capital as a value-enhancing form of mobility. Alternatively, a preference for failed founders over successful founders provides support for mechanisms related to fit and commitment (Åstebro et al., 2014; Galperin et al., 2019; Leung, 2014; Mahieu et al., 2019), rather than those related to quality. This second perspective suggests that employees depart their firms when they have extraordinary expectations and preferences that are often not aligned with or cannot be realized within their existing organizations (e.g., autonomy, flexibility, innovation). Thus, hiring firms would perceive successful founders as less likely to fit into bureaucratic structures and the culture at established firms. Also, successful founders would be seen as a greater flight risk, or more prone to leave for another venture relative to failed founders (Manso, 2016; Ucbasaran et al., 2013). By simultaneously examining the evaluation of successful and failed founders this study allows for a more complete understanding of the mechanisms driving outcomes for former entrepreneurs in the labor market.

Empirically, it is challenging to estimate the demand-side evaluation of founder experience and isolate the mechanisms driving this evaluation using observational data. Outcomes may be driven by at least three different types of theoretical mechanisms (Sørensen and Sharkey, 2014)—labor demand-side mechanisms (e.g., evaluation by hiring firms), supply-side mechanisms (e.g., selection by job candidates), and opportunity structures at preceding organizations (e.g., advancement opportunities at established firms or growth opportunities at entrepreneurial firms). To address these empirical challenges, we conducted a field experiment. Specifically, we used an audit study design which allows us to focus on the demand-side evaluation of former successful and failed founders by hiring firms, while holding constant the factors related to choices and opportunities of an individual (Kang et al., 2016; Rivera, 2012; Weisshaar, 2018). We created three identical job applicant profiles, varying only their post-undergraduate-degree work experience: wage employee at a firm, founder of a venture that signals failure, and founder of a venture that signals success. We randomly assigned one of the three profiles to 2,400 full-time entry-level software engineering positions across six metropolitan areas in the U.S.

We find that hiring firms are, on average, 43 percent less likely to callback candidates who start their career as a founder, relative to non-founders (13.6 percent versus 24.0 percent). These findings are consistent with arguments that entrepreneurial experience sends a negative signal in the labor market. But this finding alone does not explain whether this negative signal stems from entrepreneurial experience serving as a weaker, or poorer, signal of human capital and quality or from hiring firm concerns related to fit and commitment. Comparing successful and failed founders, we find that founders of a successful venture are further disadvantaged compared to founders of a failed venture (10.9 percent versus 16.2 percent), which suggests that concerns about fit and commitment are stronger drivers of our observed founder disadvantage. To contextualize our findings, we also conducted interviews with 20 technical recruiting professionals, who were unaware of our research question, experiment, or findings. The findings from our study contribute to research on entrepreneurship, human capital, and organizations. Primarily, we develop theory related to the evaluation of entrepreneurial failure and success by bridging research on the organizational spawning of entrepreneurs, wage implications of founder experience, and the demand-side evaluation of job applicants. Our theoretical and empirical approach also answers a call from researchers to incorporate the role of entrepreneurship into organizations research by considering it an element of an individual's broader career path (Burton et al., 2016).

3.2 The Evaluation of Founder Experience by Hiring Firms

Studying how organizations evaluate and manage entrepreneurial human capital brings important insights to our understanding of the structures and processes of organizations (Chatterji, 2009; Elfenbein et al., 2010; Feldman et al., 2019; Phillips, 2002; Sørensen and Fassiotto, 2011; Sørensen, 2007). Yet, theoretical mechanisms that drive the evaluation of former founders remain unclear. It has been well documented that the hiring process is rife with uncertainty (Campbell et al., 2017; Leung, 2014; Rider and Negro, 2015). Evaluators often rely on signals that may convey information about job candidates to resolve this uncertainty (Podolny, 2005; Spence, 1973). In particular, a job candidate's prior work experience and career patterns serve as a proxy to assess that candidate's quality, namely their capability and human capital, as well as their ability to fit into and remain committed to a hiring firm (Bidwell et al., 2014; Galperin et al., 2019; Leung, 2014; Rivera, 2012).

Research on hiring, entrepreneurship, and the organizational spawning of entrepreneurs offers important theoretical building blocks for understanding the demand-side evaluation of founder experience. The column headers of the matrix in Figure 3.1 provides a summary of these mechanisms from prior work, which we will discuss below, and how they should affect the demand-side evaluation of former founders by either increasing (left column) or decreasing (right column) the likelihood of former founders receiving a positive evaluation by hiring firms. As such, these mechanisms can be interpreted as providing support for founder experience as an advantage (left column) as well as a disadvantage (right column) in the hiring process. However, a focus on founder experience by itself cannot disentangle which of the two organizational perspectives—(i) mechanisms related to information asymmetry about quality or (ii) mechanisms related to concerns about fit and commitment—is driving how organizations evaluate entrepreneurial human capital.

Positive evaluations of entrepreneurial experience by hiring firms suggest that the primary function of this signal relates to quality, such that hiring firms perceive former founders to be higher quality, and relatedly more entrepreneurial and innovative than non-founders. Research on the outflow of entrepreneurs from established firms has shown that employees leave their firms when they possess superior capabilities that they cannot signal to their employers and will thus be undervalued if they stay (Anton and Yao, 1995; Hegde and Tumlinson, 2021). Therefore, if a hiring firm can accurately assess the superior quality of former founders who apply to their firm, we would expect better outcomes for former founders relative to non-founders in the labor market (i.e., an increase in the likelihood of a positive evaluation). In contrast, employees may leave their firms to become entrepreneurs when they have strong expectations and preferences that do not align with or cannot be realized within their existing organizations, such as autonomy, flexibility, and innovation. Hiring firms may consider these characteristics as "red flags" and worry that former founders would not be able to fit into and stay committed to their firms and wage employment more generally (cf. Chatman, 1991; Galperin et al., 2019; Goldberg et al., 2016; Leung, 2014; O'Reilly III et al., 1991; Rivera, 2012). Thus, if founder experience serves less as a signal of superior quality and more as a signal of poor fit and commitment, we would expect worse outcomes for former founders relative to non-founders in the labor market (i.e., a decrease in the likelihood of a positive evaluation).

We start by further discussing the mechanisms driving an increase or a decrease in the likelihood that a hiring firm positively evaluates founder experience. However, the presence of these competing explanations makes it difficult to disentangle the dominant mechanism affecting the relationship between founder experience and wage employment. Specifically, if we find evidence of a negative evaluation of founder experience, it remains unclear whether it is because this experience provides a weak signal of quality or if it signals poor fit and lower commitment. Therefore, to isolate the mechanisms driving observed effects of founder experience on subsequent labor market outcomes, we move beyond considering founder experience in the abstract and examine the effect of contextualized information about a venture's outcome—namely, venture success versus venture failure.

[Figure 3.1]

We specifically focus on early-career founders of innovation-driven (or high-tech) ventures, who typically have a science, technology, engineering, and mathematics (STEM) background. This definition of entrepreneurship aligns with our goal to better understand how firms evaluate entrepreneurial and innovative human capital. Scholars examining the organizational spawning process have similarly focused on innovation-driven firms to understand the factors that predict not only the entry into entrepreneurship but also the success of these spawned ventures (Agarwal et al., 2004; Gompers et al., 2005; Kacperczyk and Marx, 2016; Klepper and Sleeper, 2005). Furthermore, the significant failure rate associated with innovation-driven entrepreneurship results in a high transition rate to wage employment.[1] Given our

[1]While high failure rates are associated with entrepreneurship in general (U.S. Bureau of Labor Statistics, 2016), this rate is most significant for innovation-driven entrepreneurship, with some estimates surpassing 90 percent (Startup Genome, 2019). Failed entrepreneurs are not alone in seeking wage employment, with evidence suggesting that founders with relative success also make this transition (Luzzi and Sasson, 2016).

nascent understanding of the demand-side evaluation of former founders of innovation-driven ventures, our focus on early-career entrepreneurs helps provide a theoretical baseline. This focus also removes potentially confounding signals that have been shown to affect the hiring process more generally, such as employer status and social capital (Bidwell et al., 2014; Fernandez et al., 2000; Graffin et al., 2008; Phillips, 2001; Rider and Tan, 2015).

3.2.1 Mechanisms for Hiring Advantage of Founders: Capabilities and Human Capital

A relevant stream of research on the demand-side evaluation of former founders has focused on the wage effects of hired individuals with general "entrepreneurial experience," namely those who have worked for a startup or are founders, relative to those without this experience. Researchers have highlighted superior capabilities and desirable human capital developed from entrepreneurial experience (Campbell, 2013; Kim, 2018; Levine and Rubinstein, 2017; Luzzi and Sasson, 2016). For instance, in a study of the California semiconductor industry, employees from startups, relative to those from established firms, earned higher wages in their subsequent careers (Campbell, 2013). One of the posited mechanisms for this wage premium is that entrepreneurial experience serves as a signal for valuable capabilities and human capital that are otherwise difficult-to-observe, such as balanced skills, ability to leverage capabilities and resources, and ability to recognize entrepreneurial and innovative opportunities (Campbell, 2013; Luzzi and Sasson, 2016). This is also consistent with broader research on the organizational design of new ventures (Aldrich and Ruef, 2006; Stinchcombe, 1965). New ventures are resource constrained, which forces founders and their employees to not only master their core competency but also take on a wider scope of tasks (Lazear, 2005). For example, a technical co-founder will have to be a proficient developer as well as be able to effectively communicate the venture's technology and competitive strengths to internal (e.g., sales) and external (e.g., clients) stakeholders. In contrast, an employee with a similar developer role at a more established firm may possess the same technical aptitude but is unlikely to have developed these other skills.

Studies on the organizational spawning of entrepreneurs also provide evidence that smaller and younger firms enable their employees to accumulate broader human capital than older and more established firms (Sørensen, 2007). Startup-like firms are more likely to "breed" entrepreneurs and successful ventures, compared to more mature and likely bureaucratic firms, due to reduced role differentiation and specialization (Elfenbein et al., 2010; Sørensen and Phillips, 2011; Sørensen, 2007). Additionally, most former founders have experience working in close-knit teams and thus can effectively manage similar relationships at established firms (Hannan et al., 1996). Therefore, hiring firms may value former founders if they perceive that this experience yields broader human capital most commonly accumulated through founder experience (Lazear, 2004; Luzzi and Sasson, 2016).

In addition, entrepreneurs from innovation-driven ventures are associated with desirable characteristics, which may lead hiring firms to prefer former founders. Founders are thought to be "cut from a different cloth" and to possess unique positive traits (for a review, see Åstebro et al., 2014; Kerr et al., 2018). These studies suggest that founders of innovation-driven ventures are more likely to take on new challenges, successfully execute their visions, and present creative solutions despite being in a volatile or uncertain setting. The positive traits that strongly predict entry into, and persistence in, entrepreneurship can also be useful and valued by established firms; for instance, identifying worthwhile innovations in a new or rapidly changing market (Singh and Agrawal, 2011).

Hiring former founders would also align with the increasingly popular firm-wide focus on an innovative and entrepreneurial culture. Former founders of innovation-driven ventures may motivate other employees to become more innovative by exposing them to new ideas and practices. Innovative products and technologies are often developed and commercialized by entrepreneurial ventures (Schumpeter, 1951; Tushman and Anderson, 1986), and this realization has led many firms to discuss their commitment to fostering an entrepreneurial and innovative environment (Lo et al., 2020). Research on innovation and mobility provides evidence supporting this anticipated spillover effect. Specifically, researchers discuss that a way to improve innovative capacity within the firm is to hire external individuals who can source new ideas and routines from different firms (Beckman and Burton, 2008; Dokko et al., 2009; Palomeras and Melero, 2010; Song et al., 2003). Firms, especially when they perform well, often fall into competency traps and face challenges in seeking new ideas and opportunities (Stuart and Podolny, 1996; Sørensen and Stuart, 2000). Therefore, hiring entrepreneurial individuals can allow firms to access new ideas, adopt innovative practices, and reduce local search.

As summarized in the left column header of the matrix in Figure 3.1, hiring firms may value former founders to the extent that they perceive these candidates to possess superior capabilities and desirable human capital. Thus, during the hiring process, job candidates with founder experience may be evaluated more positively relative to similar job candidates without founder experience.

3.2.2 Mechanisms for Hiring Disadvantage of Founders: Information Asymmetry About Quality, and Concerns About Fit and Commitment

Despite the positive attributions about entrepreneurs, founders come from both tails of the quality distribution (Åstebro et al., 2011; Evans and Leighton, 1989; Levine and Rubinstein, 2017). In contrast to the romanticized view of new ventures emerging from entrepreneurial aspirations or innovative ideas, this empirical evidence suggests that many ventures are instead formed out of necessity—for economic need or difficulty in finding a job. While necessity entrepreneurship seems more likely for general self-employment than for innovation-driven entrepreneurship, any founder experience may be initially met with skepticism. For example, it is more difficult for hiring firms to validate skills and experiences claimed by former founders relative to wage employees for whom firms can more easily conduct a reference check (Lazear, 1981; Mahieu et al., 2019). Furthermore, while founders of innovation-driven ventures may possess broader human capital than non-founders, much of this could be seen as specific to their venture and idiosyncratic (Burton and Beckman, 2007; Sorenson et al., 2020).

This uncertainty about the quality, namely capabilities and human capital, of former founders is also related to broader organizational theory and research on evaluations in hiring. When faced with information asymmetry regarding a candidate's quality (Anton and Yao, 1995; Hegde and Tumlinson, 2021; Mahieu et al., 2019), evaluators often rely on various signals, such as education (e.g., Rivera, 2011), race (e.g., Bertrand and Mullainathan, 2004), gender (e.g., Correll et al., 2007; Rivera and Tilcsik, 2016), and community involvement (e.g., Kang et al., 2016). For individuals with wage employment experience, affiliations with current or previous employers are important (e.g., Bidwell et al., 2014; Graffin et al., 2008; Phillips, 2001; Rider and Tan, 2015). They signal, at a minimum, that these employers were willing to hire and pay the candidate. A lack of such affiliation may thus decrease the likelihood that founders, especially those early in their career, receive a positive evaluation from hiring firms.

Broader research on hiring and evaluation highlights additional disadvantages former founders may face: Uncertainty about their ability to fit into and remain committed to the hiring firm. Scholars have described hiring as a "cultural matching" process and that hiring firms are more likely to be attracted to job applicants with similar experiences, skills, and values to those of existing employees. This focus on fit is not entirely surprising when we consider that fit between employees and the hiring organization has been linked to employee satisfaction, promotion, retention, and performance (Chatman, 1991; Goldberg et al., 2016; O'Reilly III et al., 1991; Rivera, 2012). Moreover, recruiters, who are gatekeepers at the start of the hiring process, are frequently incentivized to find candidates that will be considered a good match and remain at the firm (Fernandez et al., 2000).

This fit concern may be especially salient when evaluating former entrepreneurs. Former founders often face difficulty working productively with others (Åstebro et al., 2014; Hamilton, 2000; Mahieu et al., 2019). Furthermore, a desire for non-pecuniary rewards, such as "being your own boss" (e.g., Hamilton, 2000) and flexibility (e.g., Thébaud, 2015), is a main driver for entrepreneurial pursuits. Therefore, founders may not be considered a good match by hiring firms as these individuals may be less willing to conform to established norms. These concerns are likely to be magnified in larger and more mature firms as these types of firms tend to be more bureaucratic and rigid (Kacperczyk and Marx, 2016; Sørensen and Fassiotto, 2011; Sørensen and Phillips, 2011; Sørensen, 2007; Sørensen and Stuart, 2000). In fact, these types of firms are less likely to spawn entrepreneurs, because they socialize their employees into "timid and conforming workers" (Sørensen, 2007, p. 390) unlikely to challenge the status quo and take risks.

Hiring firms generally seek job candidates they expect to be committed to the firm (Galperin et al., 2019; Leung, 2014), but former founders may be considered less committed to wage employment and therefore a "flight risk." Consistent with this notion, individuals with past founder experience are more likely to aspire to found another venture in the future. Evidence suggests that former founders are 12 percent more likely to leave wage employment to start a new firm relative to non-founders (Hyytinen and Ilmakunnas, 2007). This flight risk is salient to hiring firms given the high costs associated with employee turnover (e.g., searching for, recruiting, and training new employees) (Glebbeek and Bax, 2004; Shaw et al., 2005). In addition to the direct costs, employers invest significant resources to lower employee turnover through various retention efforts (e.g., working conditions, flexible working hours and vacation policies) (Glebbeek and Bax, 2004). Furthermore, recent research has provided evidence that when one employee leaves their firm to start their own venture they can act as "ringleaders," targeting other colleagues to join them (Shah et al., 2019). As such, these concerns around the ability to fit into and remain committed to firms could disadvantage individuals with founder experience.

As summarized in the right column header of the matrix in Figure 3.1, hiring firms may question a founder's quality given their lack of affiliation with an established employer and evaluate former founders as low in fit with and commitment to both their firm and wage employment. Thus, during the hiring process, job candidates with founder experience may be evaluated less positively relative to similar job candidates without founder experience.

3.2.3 Distinguishing Venture Success and Failure to Triangulate on Mechanisms

Thus far, we have discussed how founder experience conveys a complex signal related to quality as well as fit and commitment in ways that may yield positive or negative effects for former founders in the labor market. It is important to note that evidence suggesting positive (or negative) effects of founder experience makes it difficult to pinpoint specific drivers of these effects. Take for example evidence of a founder disadvantage, in the form of a wage discount suffered by former founders. It is challenging to discern whether this observed founder disadvantage stems from the organizational perspective related to information asymmetry about quality (capabilities, human capital) or the organizational perspective related to concerns about fit and commitment. To distinguish which class of mechanisms is driving observed effects of founder experience in the labor market, we posit that it is crucial to consider the outcome of a founder's venture, namely whether their venture succeeded or failed. Although failure is the more common outcome (Startup Genome, 2019; U.S. Bureau of Labor Statistics, 2016), it is important to consider the two outcomes together as it helps us further adjudicate between potential mechanisms.

As summarized in the matrix in Figure 3.1, we theorize about how mechanisms that would lead to an increase (left column) or a decrease (right column) in the likelihood of a positive evaluation of former founders by hiring firms vary based on whether a former founder signals a successful (top row) versus failed (bottom row) venture. Quadrants in the matrix ("Q1" to "Q4") describe why a preference for former successful founders provides support for mechanisms related to *information asymmetry about quality* (as summarized in Q1 and Q4 in the upper left and lower right), while a preference for former failed founders provides support for mechanisms related to concerns about *fit and commitment* (as summarized in Q2 and Q3 in the upper right and lower left) as the dominant organizational perspective related to how firms evaluate former founders.

As summarized in Q1 in Figure 3.1, entrepreneurial success may signal high quality, namely superior capabilities and entrepreneurial human capital, to hiring firms. This would increase the likelihood that a hiring firm evaluates founder experience positively due to quality concerns. Venture performance is a strong predictor of an earnings premium in subsequent wage employment (Campbell et al., 2012; Luzzi and Sasson, 2016). Given the high failure rates in entrepreneurship, especially innovation-driven ventures such as in the semiconductor industry examined by Campbell (2013), having a successful outcome would alleviate uncertainty related to quality. Early-career entrepreneurs lack an affiliation with an established employer—and the associated quality signals—therefore, having a successful founder experience could validate a candidate's capabilities and human capital. Hiring firms may see these founders as possessing a desirable set of skills that enabled them to achieve this success and, thus, expect them to be more likely to bring these skills and innovative ideas to the hiring firm. To the extent that the primary effect of founder experience in the labor market stems from signaling quality, we would expect former founders of successful ventures to be most preferred by hiring firms. Therefore, entrepreneurial success will increase the positive evaluation of former founders as hiring firms are trying to capture this value through their human capital strategy.

However, venture success may also magnify concerns related to whether former founders will stay committed to and fit into wage employment and the hiring firm (as summarized in Q2 in Figure 3.1). Former founders are more likely to start a subsequent new venture than those without founder experience (Hyytinen and Ilmakunnas, 2007) and hiring firms may worry that the likelihood of departure will be greater for former successful founders, who have experienced success, than for former failed founders. This is also supported by research that has demonstrated how employees surrounded by a successful former founder, relative to a failed former founder, are more prone to pursue entrepreneurship themselves (Gompers et al., 2005; Nanda and Sørensen, 2010). Further magnifying this fear, it should be easier for former successful founders to entice other employees to join them in entrepreneurship (cf. Shah et al., 2019). Relatedly, in terms of fit, hiring firms may evaluate founders of successful ventures—who were successful at being their own boss—as having lower person-organization fit with their firms (Chatman, 1991; Goldberg et al., 2016; O'Reilly III et al., 1991). To the extent that the primary effect of founder experience in the labor market stems from signaling fit and commitment, we would expect former founders of successful ventures to be least preferred by hiring firms. Therefore, entrepreneurial success will decrease the positive evaluation of former founders as hiring firms are placing more weight on fit and commitment in their human capital strategy.

Conversely, we would expect hiring firms to have fewer concerns regarding fit and commitment when evaluating a former founder of a failed venture (as summarized in Q3 in Figure 3.1). The individual could learn from this failure that they are not suited for entrepreneurship, and thus the likelihood of abandoning wage employment to try entrepreneurship again should be lower after failure than success (cf. Manso, 2016). In addition, the aftermath of a venture failure is associated with psychological (e.g., remorse, guilt, blame), social (e.g., breakdown of personal or professional relationships), and financial (e.g., bankruptcy) distress (Pollock et al., 2019; Ucbasaran et al., 2013). Understanding the general costs of failure, hiring firms are likely to worry less about the failed founders returning to entrepreneurial activities, relative to successful founders. To the extent that the primary effect of founder experience in the labor market stems from signaling fit and commitment, we would expect former founders of failed ventures to be most preferred by hiring firms, increasing the positive evaluation of former failed founders relative to former successful founders.

A failed venture, however, may heighten uncertainty around the founder's quality (capabilities and human capital), as noted in Q4 in Figure 3.1. Even if hiring firms understand that failure is the common outcome for innovation-driven ventures, this failure may confirm the assumption that some founders come from the lower tail of the quality distribution and are "pushed into" entrepreneurship (Åstebro et al., 2011; Sorenson et al., 2020). Furthermore, failed founders can suffer from a stigma associated with their failure, similar to how employees from failed firms experience status loss and lose bargaining power when they try to re-enter the labor market (Rider and Negro, 2015). As such, the stigma from failure could lead hiring firms to distrust the founder's capability and human capital, assuming that the failure is attributable to the founder's lack of skills. To the extent that the primary effect of founder experience in the labor market stems from signaling quality, these magnified quality concerns related to venture failure would lower the likelihood of former failed founders receiving a positive evaluation by hiring firms relative to former successful founders.

In sum, without considering how the likelihood of former founders receiving a positive evaluation by hiring firm varies by venture outcome, it is difficult to identify the most likely mechanisms driving the demand-side evaluation of former founders by hiring firms. Specifically, considering venture outcome helps adjudicate between (i) mechanisms related to information asymmetry about quality (capabilities, human capital) and (ii) mechanisms related to concerns about fit and commitment. Preference for successful founders over failed founders suggests that concerns related to quality (capabilities, human capital) outweigh concerns related to fit and commitment, because having a successful venture reduces information asymmetry about quality although it magnifies concerns related to fit and commitment. Therefore, information about quality would serve as the dominant organizational perspective in evaluating founder experience (Q1 and Q4 in Figure 3.1). Preference for failed founders versus successful founders suggests that concerns related to fit and commitment outweigh concerns related to quality, because having a failed venture quells concerns related to a candidate's ability to fit into and remain committed to the hiring firm despite increased information asymmetry about their capabilities and human capital. Therefore, fit and commitment would serve as the dominant organizational perspective in evaluating founder experience (Q2 and Q3 in Figure 3.1). Finally, comparing hiring outcomes for the two founder types with those of similar individuals without founder experience provides a sense of the strength of these mechanisms.

3.3 Empirical Strategy

To identify the mechanisms that help explain the evaluation of founder experience by hiring firms, it is critical to analyze how hiring firms evaluate candidates with and without founder experience but who are otherwise identical. Prior studies examining the transition of former founders to wage employment at established firms have primarily used archival data, such as census or registry data (Campbell, 2013; Levine and Rubinstein, 2017; Luzzi and Sasson, 2016; Mahieu et al., 2019; Manso, 2016). This work has been informative, especially for understanding the net earnings effect of founder experience. It has been difficult, however, to distinguish demand- and supply-side mechanisms leading to these observed differences. Observational data only allow for the identification of realized hires, and do not capture applicants who were not hired by or who did not apply to these firms. This selection on successful hires thus limits our ability to identify the extent to which demand-side evaluation processes drive differences in outcomes for former founders as compared to non-founders. In addition, the definition of entrepreneurship in research is often varied and it frequently mixes innovation-driven founders with founders of small businesses (e.g., self-employment). Founders and startup employees are also frequently mixed together, given the difficulty of distinguishing between these categories of individuals in most datasets.

We address these challenges by using a field experiment design. Specifically, we conducted an audit study, which involves sending fictitious—yet realistic—job applications to actual job openings. This methodology has been substantially used in economics, management, and sociology to capture the demand-side evaluation of job candidates (e.g., Bertrand and Mullainathan, 2004; Kang et al., 2016; Pager et al., 2009; Rivera and Tilcsik, 2016). While audit studies have been mostly used to investigate discriminatory behavior in hiring based on a candidate's ascriptive characteristics, such as gender and race, it has more recently been extended to examine demand-side effects related to candidate experiences, such as parental leave (Weisshaar, 2018). Similar to these other audit studies, we operationalize the likelihood of receiving a positive evaluation by hiring firms as receiving an initial job interview (or callback).

3.3.1 Field Experiment: Audit Study

The three main conditions are: no founder experience (non-founder), founder experience with a failed venture (founder failure), and founder experience with a successful venture (founder success). We also varied the applicant's gender to identify whether found patterns were stable for men and women.[2] Accordingly, our experiment involved sending job applications from one of the three main conditions at random to 2,400 job postings related to full-time, entry-level (requiring fewer than five years of work experience), software engineering positions in one of six different metropolitan areas in the U.S.

In field experiments, there are various choices that researchers must make including experimental design (between-subject vs. within-subject), population of interest, and manipulations. These choices could limit the generalizability of findings. Prior to our study, we consulted with various expert informants to help us make choices that allowed us to simultaneously advance theory and retain external validity. This group consisted of 4 software engineers with 2-4 years of experience in software engineering (who share a similar background to our fictitious job candidates), 4 hiring managers or recruiters with 5-10 years of experience recruiting for technical positions, and 2 individuals experienced with preparing job candidates for the job market, one with no specific industry concentration and the other with entrepreneurship and software engineering experience.[3] We also discussed key design choices with various academic researchers studying entrepreneurship and labor markets, and received feedback on application materials. In terms of experimental design, we used a between-subjects design due to both ethical and practical reasons (Lahey and Beasley, 2018; Vuolo et al.,

[2] A discussion of these results can be found in Appendix B.

[3] We had access to these informants through pre-existing connections and referrals. None of these individuals are one of our 20 informants for our post-experiment interviews.

2018)—most importantly, to minimize the within-employer time burden and to avoid detection (Kang et al., 2016; Rivera and Tilcsik, 2016; Weisshaar, 2018). In discussing the application review process with recruiter informants, it was clear that the likelihood that the same person would review applicants for the same, or a related, job was non-trivial, especially at small and medium-sized firms. The field experiment's general design and conditions were pre-registered at the Open Science Framework (`https://osf.io/kxj3f?view_only=d06eb25fc08540c990854035ed603023`) and approved by an institutional review board before the job applications were sent.

An important design choice was our decision to focus on early-career entrepreneurs, especially given recent evidence that founding a new venture most commonly occurs in the later stage of one's career (Azoulay et al., 2020).[4] Apart from our earlier theoretical reasoning that this focus provides a clearer baseline, our focus on early-career founders was also driven by empirical and policy-related considerations. Empirically, our conversations with recruiter informants highlighted that the job search and hiring processes for an individual later in their career differs substantively from those earlier in their career. Mid- and later-career job seekers primarily find employment opportunities through their social networks and search firms, whereas early-career individuals routinely apply online. Thus, an audit study design best approximates the job search process for early-career individuals whereas it represents an abnormal job search strategy for mid- and late-career individuals. In terms of policy, there have been concentrated initiatives to promote and provide resources for early-career individuals to launch ventures. The fact that the number of states reporting K-12 standards for entrepreneurship education has more than doubled between 2009 and 2015 (Marich, 2015) and one-third of U.S. incubators are

[4]Other studies examining the relationship between age and entrepreneurship have offered an inconsistent depiction of the modal type. For example, Liang et al. (2018) document that a decrease in a country's median age increases new business, using a cross-country entrepreneurship data. Ng and Stuart (2016) find that the founding rate for high-potential startups peaks at early 30s (at approximately 8 years after college) and begins to fall off thereafter. Evans and Leighton (1989) find that the probability of entering self-employment is independent of age for men who are under 40.

housed on university campuses (Kauffman Foundation, 2013) underscores this trend. Early-career setbacks also have a long-term and substantive impact on an individual's career (Altonji et al., 2016; Oreopoulos et al., 2012; Sorenson et al., 2020).

3.3.2 Application Materials

Job applications in our study consisted of a resume and a cover letter. The application materials varied across conditions in the following two areas: (1) applicant contact information—first name, address, e-mail, and phone number; and (2) applicant work experience—applicant company name, job title, and language used to signal venture outcome (failure versus success). Other information (e.g., work responsibilities, education, interests, skills) remained identical across all conditions. Each of our fictitious applicants had worked for one firm and completed approximately three years of full-time work experience, with the same major day-to-day activities; listed the same skills and interests; and participated in the same extracurricular activities. This information was detailed in the applicant's resume and summarized in the accompanying cover letter. Table 3.1 provides a summary of the information used in each resume across conditions.

[Table 3.1]

In terms of the applicant's contact information, for each applicant-city pair we listed a local address[5] and a phone number (with an area code used in the metropolitan area) on the resume. We did this to remove potential geographical barriers to a job applicant receiving a callback. For example, an employer may be wary of a potential applicant moving across the country for a job and possibly asking to cover the costs of the interview and relocation, or the employer may need a new hire to start quickly.

[5]Addresses were chosen based on the median rental price for a one-bedroom apartment in the focal city. For each address, we used an apartment number that did not exist to help ensure that spam mail was not sent to a real address.

If similarly qualified applicants are local, a non-local applicant would have a lower chance of receiving a callback relative to a local candidate. A unique e-mail address was used for each applicant-city pair to keep track of the resulting data. We consulted with our informants to ensure the external validity of our materials and conducted pre-tests to ensure our manipulations accurately captured entrepreneurial success and failure. For pre-tests, participants reviewed application materials for one of the three founder conditions, and were then asked to identify whether the applicant is a founder; and, whether that founder's venture was successful versus failed. Overall, the combination of work experience details in our resume and cover letter, which we will further describe below, served as salient manipulations of founder experience, with the majority of pre-test participants being able to correctly identify the founder condition assigned to them.[6]

We chose first and last names that are not associated with low or high socioeconomic status (Gaddis, 2017) to enhance generalizability and avoid confounding effects of socioeconomic status which may correlate with the mechanisms we are testing. We pre-tested these names to intentionally choose the names that subjects classified as being white and middle-socioeconomic status. The same last name was used across all conditions.

In terms of applicant experience, the only differences across the job applications related to our experimental conditions. To create salient and reliable manipulations, we varied multiple elements related to the applicants' past employment experience on the application materials—company name, job title, the language used to signal venture outcome, and a description of the founder's salary (Rivera and Tilcsik, 2016, pp.1104-1105). Applicants in the two founder experience conditions (failure and success) listed themselves as a Co-Founder & CTO of their venture, and the job title

[6]Using Amazon's Mechanical Turk, we recruited 400 participants online. The vast majority of the participants (92 percent) were able to distinguish between founders and non-founders, while 96 percent of those who were assigned to one of the two founder conditions were able to distinguish success and failure conditions.

"software development engineer" was used in the non-founder condition.[7] For many startups, especially for innovation-driven ventures, a founder commonly holds the title of Chief Executive Officer (CEO) or Chief Technology Officer (CTO). We chose the CTO title because the CEO title has more ambiguity and variance in responsibilities and experiences; it is unclear what kind of job title would be most suitable as the counterfactual for the CEO title. However, "Co-Founder & CTO" as a job title for the treatment conditions has a clearer counterfactual case as many technical founders primarily function as software engineers—this similarity in responsibilities was confirmed in our discussions with our informants. We position our founder candidates as completing a software engineering role without mention of other non-technical duties. In addition to the methodological benefits, using the two roles are most closely aligned with our motivation for this research. First, it aligns with our goal to focus on innovation-driven entrepreneurship. Theoretically, we can more closely contribute to organizational spawning research which often concerns the spawning of innovation-driven ventures. Empirically, it is a core type of entrepreneurship considered by college-aged individuals. Second, software engineering is one of the most in-demand professional fields (Stansell, 2019), which enabled us to find the necessary number of jobs to apply to in a timely fashion.

In the failure condition, failure was signaled on the resume by stating "failed to secure the necessary funding and are ceasing operations." Since we did not want recruiters at hiring firms to think that the failed founder was pushed into entrepreneur-

[7] One may argue that the two roles are too distant, and that CTO is a more managerial role and thus a CTO may not be doing the programming. Yet, based on our pre-study interviews with software engineer informants and popular press discussing this issue, CTOs at a startup typically spends "all [their] time hacking [coding]" in the early days and "about 80 percent of [their] time hacking [coding]" when they get a small team of up to six people (Daugherty, 2015; Helmig, 2017). Also, searching profiles of individuals with "Co-Founder & CTO" as the job title on an online career networking platform shows that the primary function and description of these individuals mirrored those of software engineers. These individuals share similar technical tasks and are likely to build up similar programming skills as software engineers at more established firms. Therefore, the tasks and skills of a CTO at new ventures more closely resemble those of software engineers at established firms, rather than those of a CTO at established firms.

ship (i.e., necessity entrepreneurship) (Åstebro et al., 2011; Levine and Rubinstein, 2017) and instead be thought of as an individual who could have joined wage employment, we also added a bullet "able to pay myself a salary to cover necessary expenses." Conversely, in the success condition, success was signaled on the resume by stating "successfully sold the firm for $3 million." We also added a resume item, "able to pay myself a market competitive salary" as a balance to the salary information in the failure condition. In both cases the former founder was transitioning from their venture and looking for employment.

Related to design choices, an alternative for the failure condition would have been not to admit the failure. However, the common wisdom is that former founders ought to discuss their venture failures in resumes and to describe it as a learning experience in interviews (e.g., Franco, 2015; Jobscan, 2016). This language was also consistent with what we heard from our informants tasked with preparing job candidates for the job market. They indicated that they encourage former founders to be honest and believe that discussing failure openly is beneficial and that discussing one's failures is often a routine question in the interview process. We were also advised against blaming the failure on the founder or a team member and instead on a financing issue, a common reason for startup failure. For the success condition, the choice of $3 million[8] stems from our informants indicating that not listing an amount would be met with suspicion, whereas lower amounts brought their success into question and higher amounts elicited questions about whether the person would need to work again. The non-founder condition described the applicant as working for an actual firm involved in the same business as our fictitious startup and with the applicant having identical responsibilities as our founder conditions. Consistent with being a

[8]Having sold the startup for $3 million may be considered a substantive amount but note that the candidate is a co-founder and it is reasonable to conclude that the success cannot be solely attributed to the founder. Furthermore, after taxes and fees this split amount is only a bit higher than the bonus and equity packages an engineer can accumulate at a leading technology firm over the same number of years.

technical co-founder (and a software engineer, in our non-founder condition) we listed only technical responsibilities, which were identical on all resumes.

A challenge to using an audit study design is the lack of a credible online profile and general presence (e.g., news articles) of the candidates. In our context, this also extends to a lack of online presence for the founder's firm. Although it is possible to create a basic web presence, it would be nearly impossible to make this presence credible, especially for the success condition. Recruiters may expect to find information about the venture online, with one informant telling us that while they do not always search for candidates online, the lack of online presence for their venture would lead them to believe the candidate's venture was a failure. This fact is in line with our failure condition; however, it imposed a challenge to our success condition. Therefore, for the success case, we put the fictitious venture name in quotations and stated in the cover letter and resume that the sale of the venture was almost complete, but until it was completed, the conditions of the sale did not allow our applicant to publicly announce the sale and instead a pseudonym was being used. In addition to conducting pre-tests regarding our manipulation, we also asked online participants, as well as recruiter informants, whether using a pseudonym would appear as strange or suspicious. Both our pre-tests and pre-study interviews with recruiter informants dispelled these concerns.[9]

Each job application included a personalized cover letter, which included the position title and the name of the firm being applied to in the opening paragraph. Recruiter informants admitted to us that while they often do not review cover letters, if one was missing or lacked personalization, they would view this negatively, indicating a low level of interest. Therefore, we decided to include this level of per-

[9] In the pre-tests with 400 participants, we asked if the participants who received success or failure condition find not disclosing the name of the company (success condition) or using a name that cannot be tracked (failure condition) suspicious. Approximately 80 percent of the participants responded that they did not find it suspicious or strange. Those assigned to a failure case reported that it is reasonable not being able to find web presence of a company that had failed.

sonalization. This choice would not affect the internal validity of our findings, since it would be constant across conditions; however, it strengthens the studies generalizability as it is possible that the types of employers that would give a callback to an applicant without this personalization may be substantively different from those employers who would not. In the end, our goal was to mimic the typical job application process for the focal positions in our study as closely as possible.

3.3.3 Participants: Recruiters at Hiring Firms

The participants in our study were recruiters[10] (e.g., human capital/resources representatives) who review job applications submitted for a given job opening and evaluate the applications to determine who should continue in the process and receive an interview.

Although this methodology involves a cost to the participants, namely a loss of time, we took marked steps to ensure that these costs were minimal. Our recruiter informants revealed that a recruiter spends about five to ten minutes on a candidate that receives an interview. For many positions, a substantial number of candidates are never reviewed and only a very small percentage of candidates are chosen for an interview. Based on these estimates and assuming every application was reviewed to this full extent, it would take between 200 to 400 hours across the pool of recruiters in our study to review the 2,400 job applications we submitted for this field experiment. Using data from `www.payscale.com`, a mid-career recruiter (five to ten years of experience) earns an average total compensation of $55,000.[11] Therefore, at the high end—assuming ten minutes per each of the 2,400 candidates—the total cost imposed to complete this research was $10,600 (or $4.42 per firm).[12] We also responded to

[10] For the remainder of the paper we use "recruiters" to refer to the individuals who screen applicants in the initial stage of the hiring process. Depending on the firm, these individuals could go by various titles. Further, this individual could also be the hiring manager for the position though less likely as firms frequently have recruiters who assist in the early stages of the hiring process.

[11] https://www.payscale.com/research/US/Job=Recruiter/Salary

[12] It could also be argued that there was a cost to those candidates that did not receive a callback

recruiters who indicated interest in our candidates in a timely fashion, as detailed below, to further minimize any additional time investment on the part of the firm. We strongly believe that the results of this research will offer benefits to individuals who need a better understanding of how founder experience may affect their career, organizations who want to better understand how human capital is evaluated, and policymakers who are interested in entrepreneurship programs.

3.3.4 Application Process

We applied to jobs over a consecutive 28-day period in the summer of 2018. All applications were completed by the authors to ensure consistency in the application process and timely completion. Applying to jobs over a long cycle introduces the possibility of noise stemming from labor market fluctuations that could substantially affect the results. We sourced job openings posted on a major online job search engine platform.[13] We applied to the position following the application instructions for each job opening, simulating a realistic job applicant's strategy. A job entered our risk set if it met the following criteria: it was posted within the last 30 days, listed as entry-level, listed as full-time, and located within 25 miles of the metropolitan area of interest (Austin, TX; Boston, MA; Chicago, IL; Los Angeles, CA; New York, NY; and San Francisco, CA). Each job that fit these criteria was checked by both researchers to ensure that the employer was looking for applicants with a software engineering background. When multiple jobs at the same firm fit our criteria, we chose the most recently posted jobs, and then chose at random if multiple jobs were still available. We then stratified the job openings in terms of the geographic location

due to our candidate being selected over another applicant. However, we were told that individuals who withdraw or do not respond after the initial interview request are most frequently replaced.

[13]A benefit of this sourcing strategy is that the jobs advertised include positions submitted by employers as well as other open positions aggregated from other career sites and recruiter listings. Thus, we are able to come up with a comprehensive list of employers and open positions. A key distinction is that for the latter set applicants cannot apply through the job search platform and instead need to apply through the employer's career portal or human capital management platform (e.g., Workday, Lever).

and employed block randomization to assign each job opening to each candidate. This block randomization ensured that we achieved balance across experimental conditions within each city block.

After a job was assigned to an applicant profile it could be skipped, with the two most common reasons being that the job posting was no longer available and that the job description available during the application process changed and no longer fit our criteria (e.g., it was listed in one of our six cities but was actually for another city). When a job was skipped that firm was re-entered into our risk set. Table 3.2 shows the distribution of job applications submitted across the six metropolitan areas for each experimental condition.

[Table 3.2]

3.3.5 Measures of Interest

We checked the e-mail and voicemail accounts for each applicant-city pair daily to make sure that data were being recorded consistently and to immediately respond to hiring firms that the applicant was no longer interested. A callback was considered if it occurred within 60 days from the focal job application date. The unit of analysis is the job application and the main outcome variable is *Callback*. This variable is an indicator variable that takes the value of 1 if the hiring firm contacts the job applicant for an interview, and 0 otherwise. Contact by hiring firms was primarily through e-mail, with only a handful occurring via phone call. These e-mails typically came from a recruiter at the firm and followed a similar pattern, stating their interest in the applicant and requesting to schedule a 30- to 60-minute phone interview (see Figure 3.2 for an example).

[Figure 3.2]

In eight cases firms reached out to request the completion of a technical challenge, such as writing code to solve a problem, before an initial interview. In these cases, we e-mailed back and asked the recruiter whether this request was being sent to all applicants or to shortlisted applicants as the next stage of the interview process. We coded *Callback* as 1 if the technical challenge was the next stage of the interview process and as a 0 if it was sent to all applicants. After a callback was received and noted, we promptly e-mailed the firm representative back stating that the applicant was no longer interested and wanted to withdraw from consideration for this job and any future jobs. The same message was used in all communications across all conditions. We also kept track of the dates for all communications, specifically, the days between the job application and a response (*Days to Callback*).

The main independent variables are indicator variables identifying the respective experimental condition. The indicator variable, *Founder* takes the value of 1 if the applicant started their career as a founder (failure or success) and 0 if the applicant was not a founder. Then, we created indicator variables to represent each of the conditions: *No Founder Experience* for applicants with no founder experience, *Founder Failure* for applicants with founder experience who failed, and *Founder Success* for applicants with founder experience who succeeded.

To account for any geographic variation in hiring practices that can influence hiring decisions of the applicants, we control for the location of the job using six indicator variables that take the value of 1 if the job posting was from the particular metropolitan area, and 0 if otherwise: *AUS* for Austin, TX (the reference category); *BOS* for Boston, MA; *CHI* for Chicago, IL; *LA* for Los Angeles, CA; *NYC* for New York, NY; and *SF* for San Francisco, CA.

We also collected a set of variables on hiring firm characteristics that could influence a recruiter's evaluation of founder experience. Founding dates for the firms in our sample were collected from various online resources (*Firm Age*). Founding year could not be found for 31 firms. Additionally, we matched firms in our sample to its corresponding two-digit North American Industry Classification System (NAICS) code. Our sample consists of firms in 21 unique industries using this classification scheme. A separate industry code was used for firms that could not be clearly categorized according to this classification.

3.3.6 Summary Statistics

The summary statistics of key variables are shown in Table 3.3. In total, 411 of the 2,400 applications received a callback. The average age of the firms was 27 years (median of 15 years), and this variable is skewed heavily to the right. Approximately 37 percent of firms were 10 years of age or younger. On average, callbacks were received nine days after the application was submitted. Although we do not know the base rate of the gender of the recruiters at the firms, recruiters reaching out to candidates who received a callback were approximately even in terms of gender.

[Table 3.3]

Table 3.4 provides a comparison of key variables across conditions to assess the integrity of our randomization. Pairwise t-tests of *Days Since Job Posted* and *Firm Age* demonstrate that there are no statistically significant differences across the founder conditions ($p < 0.05$). Pairwise chi-squared tests of the industries of the firms applied to also do not differ significantly ($p < 0.05$). Furthermore, Figure 3.3 plots the distribution of each of these variables, where a box plot is accompanied by the kernel density in the shared area. Together, these results give us confidence that our random assignment yielded a sample that is balanced on key observable characteristics across our conditions. We present the plots of all of our results below and provide the supporting tables in Appendix A. Given that our treatment is randomized and these characteristics are balanced across conditions (as shown in Figure 3.3) controls are not strictly necessary; however, we include regressions with and without controls because the inclusion of controls can improve point estimate precision.

[Table 3.4]

[Figure 3.3]

3.4 Results

3.4.1 Founder Experience and the Likelihood of Receiving a Callback

We first look at the evaluation of former founders by hiring firms evidenced by the callback rate for each founder condition. Here, we group founders regardless of their venture outcome using the binary variable, $Founder$. Figure 3.4 compares callback rates for non-founders versus founders. We find that having founder experience substantively lowers the number of callbacks received. The callback rate for non-founders was 24.0 percent. It is important to note that this is a high callback rate. However, as one recruiter stated in their reply to our message rejecting their request for an interview, "it is a seller's market." This sentiment is also supported by available labor market statistics. For example, in 2015 (the year our applicant graduated from college), there were approximately 60,000 computer science graduates and approximately 527,000 related openings, a ratio unparalleled by other industries or specialties (Kessler, 2017; Stansell, 2019). Therefore, we should expect our baseline callback rate in this context to be much higher than in other contexts. Furthermore, what is important for our focal research question is how callback rates differ across conditions. We found that the callback rate for founders was 13.6 percent. Therefore, founder experience resulted in a callback rate that is approximately 43 percent (more than 10 percentage points) lower than not having founder experience, all else equal

($p < 0.001$). These results provide causal evidence that early-career founder experience is evaluated negatively by recruiters during the hiring process in our context.

[Figure 3.4]

[Table 3.5]

Comparing the callback rates for founders and non-founders thus suggests that former founders are evaluated less favorably by hiring firms, which generally indicates that this experience leads to uncertainty related to quality and/or concerns about fit and commitment, as we summarized in the right column header of Figure 3.1. While we find evidence for an early-career founder disadvantage, it remains unclear whether the demand-side evaluation outcome is driven by an organizational perspective on quality (i.e., information asymmetry about the former founder's capabilities and human capital), or an organizational perspective on fit and commitment (i.e., concerns about the former founder's ability to fit into and stay committed to wage employment and the hiring firm).

To disentangle these mechanisms, we next examine the heterogeneous effects of founder experience as a function of venture success versus failure. Figure 3.5 shows the average callback rate across our three main conditions: no founder experience, founder failure, and founder success. The result for the non-founder condition is the same as seen in Figure 3.4, with a callback rate of 24.0 percent. We find former founders whose venture failed have a higher callback rate than founders whose venture succeeded. Specifically, the callback rate for the founder failure condition was 16.2 percent, while the callback rate for the founder success condition was 10.9 percent. Therefore, these results show that while all founders are disadvantaged in the initial evaluation stage of the hiring process relative to non-founders, founders of failed ventures fare significantly better than founders of successful ventures, resulting in a callback rate that is approximately 48 percent (or more than 5 percentage points) higher ($p < 0.01$).

Overall, comparing the likelihood of receiving a positive evaluation by hiring firms across the three founder experience conditions, considering venture outcome, enables us to disentangle the relative strength of mechanisms related to founder advantages and disadvantages. Specifically, these results suggests that employers are more concerned about fit and commitment, than about quality, when assessing former founders. This is consistent with our theorized explanations summarized in Q2 and Q3 in Figure 3.1. Preference for founders of failed ventures relative to successful ventures provides evidence that the concerns related to fit and commitment outweigh the advantages related to quality (capabilities, human capital). In short, managing the inflow of entrepreneurial human capital, which is reflective of structures and processes within firms, is most strongly driven by concerns about fit and commitment rather than information about the quality of former founders.

[Figure 3.5]

[Table 3.6]

3.5 Post Hoc Analyses

3.5.1 Are Successful Founders Seen as Overqualified?

An important alternative explanation to our findings is that our founder success condition is discounted relative to our other conditions because former successful founders are seen as overqualified or less likely to accept early-career jobs (cf. Galperin et al., 2019). As summarized in Q1 in Figure 3.1, prior entrepreneurial success may increase the likelihood of former founders receiving a positive evaluation from hiring firms because it signals superior capability and entrepreneurial human capital to hiring firms (Campbell, 2013; Luzzi and Sasson, 2016). Also, while unlikely, using the CTO title may lead recruiters to believe that former successful founders should be placed in a role with more leadership responsibilities. In short, even though the jobs we applied to are in line with the candidate's experiences, having been successful founders may lead recruiters to believe their capabilities and human capital are too high for these positions.

To unpack this alternative, we used our empirical design to apply to 400 additional jobs. The key difference in this application process relative to that of our main results is that we only applied to mid-level jobs (typically requiring at least five years of experience and many describing a leadership role), whereas we only applied to entry-level jobs (requiring fewer than five years of experience) in our main study. The callback rate for former successful founders to mid-level jobs was 6.3 percent, which is approximately 40 percent (or 4 percentage points) lower than the callback rate for these same applicants to entry-level jobs, 10.9 percent ($p = 0.023$). This substantively lower callback rate does not support the argument that recruiters found the successful founders as overqualified.[14]

3.5.2 Do Founders Receive Callbacks for More Desirable Jobs?

To provide further insight into our main results we analyzed whether the job desirability differed across conditions. We had three software engineers, who closely matched

[14]There is no reason to believe that the base rate of receiving a callback for an entry-level job would be substantively different from that of a mid-level job. However, to make a direct comparison in the base rate, we conducted an ex post exploratory analysis near the end of the experiment period and applied to mid-level jobs with our non-founder condition. To reduce the cost to employers for this supplementary analysis and ensure that the new applications were sent not too long after the main experiment, we limited it to 20 percent of the targeted sample, resulting in 80 jobs. The callback rate for the non-founder condition was 13.8 percent for mid-level jobs, a rate that is approximately 2.2 times higher than that of the successful founder ($p = 0.020$). This provides further support that the results from our initial field experiment were not driven by recruiters believing that successful founders were overqualified for the positions.

the profile of our fictitious job applicant, independently rate each job that one of our applicants received a callback from. Jobs were rated on a 1 to 5 scale with 1 indicating that they had no interest at all and a 5 indicating that they were extremely interested. These engineers were unaware of which jobs corresponded to which condition. Across the three engineers and across each job type the average rating was 2.9. The average rating for the non-founder condition was substantively the highest at 3.0. The average rating for the founder failure condition was 2.8 and the average rating for the founder success condition was 2.9. Although the non-founder condition received the highest average score, we do not see these differences as substantively meaningful. Statistically, using a pairwise comparison, the only difference of note is between the non-founder condition and the failure condition ($p = 0.069$). These results confirm that there is little difference in job desirability across the conditions and that it is not the case that former founders, especially former successful founders, are receiving interviews for the most desirable jobs.

3.5.3 Firm Age and the Demand-Side Evaluation of Founder Experience

Researchers studying the organizational spawning of entrepreneurs have consistently found that a firm's age is strongly correlated with entrepreneurial entry and performance, with employees from more established firms being less likely to become founders and experience entrepreneurial success compared to employees from younger firms (Kacperczyk and Marx, 2016; Sørensen and Fassiotto, 2011; Sørensen and Phillips, 2011; Sørensen, 2007; Sørensen and Stuart, 2000).[15] The demonstrated relationship between firm age and the organizational spawning outcomes informs that a

[15]These studies have also examined firm size along with firm age and found consistent results due to their strong correlation between these measures (Sørensen and Phillips, 2011; Sørensen, 2007). Unlike these studies that use registry data or publicly-accessible firm data, many of the hiring firms in our sample are private companies. Therefore, while firm age information is available via multiple sources, firm size information is not.

firm's processes and structures are strongly tied with its employees' transition to, and success with, entrepreneurship. Specifically, a firm's age is argued to affect different skills, knowledge, and cultural norms and values employees can attain at their organizations (Sørensen and Fassiotto, 2011). For example, older firms—characterized with rigid job specializations, hierarchical structure, and emphasis on rules and routines—are more likely to exploit existing competencies and engage less in exploring new ideas and practices than younger firms, which tend to have more positive attitude towards risks and attaining challenging goals (Gompers et al., 2005; Sørensen, 2007; Sørensen and Stuart, 2000; Xu and Ruef, 2004). With respect to our research question, recruiters working at younger firms may be more inclined to see founder experience as fitting in with the culture of their firm and to value this experience relative to recruiters at older firms. They are also more accustomed to high turnover rates, and thus may have fewer concerns related to commitment. Therefore, given that fit and commitment were the dominant mechanisms driving our main results of a founder disadvantage, we should expect more similar callback rates for candidates with and without founder experience when applying to positions at younger firms. To test this, we exploited the natural variation in firm age within our study to determine whether callback rates for candidates with founder experience varied as a function of firm age.

Figure 3.6 presents the likelihood of receiving a callback for each of the three main founder conditions, separately for older firms—with firm age greater than 10—and younger firms—with firm age less than or equal to 10. For older firms, the evaluation pattern remains similar to the main results presented. Non-founders were the most likely to receive a callback (22.9 percent), followed by failed founders (14.1 percent), followed by successful founders (7.4 percent), with these differences remaining statistically significant ($p < 0.001$). For younger firms, the most preferred applicant is also the non-founder (25.8 percent). However, the pattern for founders is a bit different when we consider recruiters from these younger firms: Callback rates for both failed and successful founders are higher and statistically equivalent, 19.8 percent and 17.0 percent respectively ($p = 0.382$). Relative to the non-founder condition at younger firms, there is an overlap in the confidence intervals between the callback rate for non-founders and failed founders ($p = 0.095$). Comparing across younger and older firms within conditions, there is only a statistically significant difference in the successful founder condition. Younger firms are much more likely than older firms to callback a former successful founder ($p < 0.001$). These results demonstrate that much of the founder discount is driven by recruiters at older firms who show a strong evaluative preference for non-founders, as well as an evaluative preference for failed founders over successful founders. Younger firms, which share more similar values and practices with entrepreneurial ventures, are likely to have fewer concerns related to fit and commitment of former founders.

These results on firm age contribute to the debate in the organizational spawning literature regarding the presence and role of bureaucracy. Established research consistently suggests that bureaucratic firms are less likely to spawn entrepreneurs. However, it remains unclear whether the spawning is driven by the treatment effect (e.g., bureaucratic organizations do not offer resources and practices for entrepreneurship) or selection effect (e.g., less entrepreneurial individuals choose to enter bureaucratic firms). Our study provides evidence for selection as a driver of our observed results. Older, and likely more bureaucratic, firms evaluate former founders less favorably. Therefore, firm age is linked to not only the spawning of entrepreneurial ventures but also the hiring of former entrepreneurs. As in the organizational spawning literature, understanding the boundary between entrepreneurship and wage employment—in our case, the reverse process (or the inflow of human capital)—offers insight into organizational processes and structures related to entrepreneurial human capital.

[Figure 3.6]

[Table 3.7]

3.6 Interviews with Recruiters: Face Validity for Main Results

We interviewed 20 technical recruiters to further explore whether anecdotal evidence from these interviews is consistent with the theoretical mechanisms put forth to explain our results (Rivera, 2012). These recruiters were not aware of our research question, experimental design, or findings. These individuals are tasked with identifying and screening job candidates for technical positions (e.g., software engineering) on a daily basis, and spoke about their experience with recruiting entry-level hires. We recruited participants through an online professional networking platform. We employed theoretical sampling (Small, 2009) to select recruiters with varying backgrounds (e.g., level of experience, industry, firm type, and gender) to best represent the recruiters from our field experiment. While most recruiters screen applications for their firms, four of the recruiters worked at technical-focused search firms. Interviews with search firm recruiters offer a more general view of industry recruiting trends that may not be salient during interviews with recruiters at a specific firm. Information about the interviewed recruiters and their firms is summarized in Table 3.8.

[Table 3.8]

Each interviewee was read a verbal consent prompt that stated our interest was learning more about the "recruiting process for technical positions, such as software engineers." Interviews, conducted via phone calls, were semi-structured and lasted approximately 20-30 minutes. We asked them questions regarding their recruitment process of technical positions and then their experience with and evaluation of former founders during the recruitment process. Recruiters reported very similar recruitment practices, which involved directly sourcing potential applicants for openings, analyzing referrals, and reviewing unsolicited applications (i.e., applications via the firm's website or human capital management platform). On average, unsolicited applications were about 40 percent of the total applications received for an opening. The remaining applications were either sourced by the recruiter (34 percent) or employee referrals (26 percent). Each recruiter reported experience evaluating former founders for these positions. One interviewee highlighted that they are seeing more early-career applicants with founder experience (Recruiter 11) and another that former founders are more prevalent for technical roles relative to non-technical roles (Recruiter 9). This information is in line with our earlier discussion with informants that unsolicited applications are the most singularly common mode for applying to entry-level roles and that recruiters for entry-level technical positions are familiar with evaluating former founders.

3.6.1 Discussions Related to Fit and Commitment

Recruiters were concerned about whether former founders could fit into their firm and wage employment more generally. Recruiters noted that assessing a candidate's fit is a crucial part of their evaluation, and that values and attitudes of founders would be different from those of wage employees. Recruiter 7 stated that she assesses founders against her "culture flag." Recruiter 3 stated that founders rarely passed his screening due to concerns about fitting into wage employment: "Founders look like aliens to people." Recruiter 8 described her impression of former founder as a misfit for her firm, "[Former founders] are afraid of politics, hate the documentations they need to go through, and don't seem to understand why there is a structure here. They are from a chaotic environment and may expect peaceful working conditions here. But that's not always the case."

Other recruiters shared these concerns about fit and believed that former founders would not become a "good corporate citizen" (Recruiter 3). Many also worried about former founders not being able to cope well with upper-level managers at a more bureaucratic workplace. Recruiter 5 said former founders "may not be able to receive training from more senior developers [and] may not know about best practices of working professionally." Similarly, Recruiters 7 and 16 both indicated that former founders would not be able to work around the "red tape" present in wage employment.

Concern regarding fit seemed stronger for former founders of successful ventures. Recruiter 19 worried that former successful founders would feel uneasy taking directions and being part of a team. "Entrepreneurship is a mentality. We worry that the success cases will feel confined or get bored," said Recruiter 7. Recruiter 13 said she screens out job applicants with successful ventures entirely but evaluates failed founders more positively, "Successful founders are cocky. You can't undo success...This makes it hard for successful founders to land on a job. We are scared they won't settle into their role. Few [founders] even get an interview but the ones that have are failures."

Commitment concerns were also commonly discussed by recruiters. Our sample of recruiters discussed former founders, especially the successful ones, as flight risks and thus less committed to the firm. Many recruiters described these candidates as "jumpy" (Recruiter 4). They assess whether job candidates are the ones "who can have longevity in roles" (Recruiter 12) given that "it is expensive to hire technical talent" (Recruiter 15). Recruiter 2 stated that former successful founders would have a greater flight risk: "I understand that they apply for stability but worry they may suddenly leave. They may go all in for new ideas and opportunities." Recruiters also expressed concern about founders poaching other employees (Shah et al., 2019). Recruiter 7 discussed a recent example where a former successful founder who was hired left quickly to found a startup, taking with them a long-time employee from the firm.

3.6.2 Discussions Related to Capability and Human Capital

While failed founders elicited more concern regarding quality, in particular capability and human capital, many recruiters stated that this could be figured out in subsequent stages of the hiring process. These recruiters mentioned that founder experience, in general, engendered uncertainty regarding the founder's quality. Yet this only occurred when discussing former failed founders, with no recruiter expressing quality concerns for former successful founders. Recruiters 11 and 14—both from technology search firms for younger client firms—indicated a preference for successful founders because of their quality signal. Consistent with human capital research and the popular depiction of founders, several recruiters acknowledged penchant for innovation and entrepreneurial attributes of all founders. "[Former founders] are more adventurous, creative, driven" said Recruiter 10. Recruiters did not specifically penalize founders whose venture failed, as they discussed that most startups fail and that many factors affect the survival of a venture. Recruiter 15 noted that there are positive aspects of venture failure and success: "A failed founder can tell you what they learned whereas a successful founder can tell you why they're great." Other recruiters echoed this common trope that founders can learn a lot from failure, as Recruiter 12 described, "In fact, during the screening interviews, I always ask: "tell me a story about your failure. How did you approach your situation and how did you react to that?" Failure demonstrates learning experience, resilience."

Overall, these semi-structured interviews lend face validity to our main findings from the field experiment by providing illustrative and real-world examples that are consistent with our proposed theoretical mechanisms related to fit and commitment concerns. From these interviews, recruiters did not emphasize quality concerns related to founder experience, especially at the initial stage of the hiring process.

3.7 Discussion

Examining how founder experience is evaluated by hiring firms deepens our understanding of organizations' human capital strategy and individual career trajectories. We focus on the demand-side evaluation of entrepreneurial success and failure, namely how hiring firms evaluate former successful and failed founders as job candidates. In doing so, we bring together research on careers, entrepreneurship, and organizational spawning to theorize about the most likely mechanisms driving how organizations evaluate founder experience at the initial stage of hiring. Causal identification of whether the demand-side mechanism relates to an increase or decrease in the likelihood of former founders receiving a positive evaluation by hiring firms necessitates that supply-side mechanisms remain constant. We achieve this by using a field experiment design and find causal evidence that early-career former founders are disadvantaged in the initial stage of the hiring process. To test whether the mechanisms affecting this evaluation are uncertainty related to quality, in particular capabilities and human capital, or concerns related to fit and commitment, we compare former founders who discuss their experience as a failure versus a success. The observed preference for failed founders over successful founders points to how concerns related to fit and commitment are the dominant organizational perspective regarding the evaluation of founder experience in the hiring process. Furthermore, we find evidence that this founder disadvantage is more pronounced among older hiring firms than younger firms, offering further insights into organizational structures and processes.

The organizational spawning literature has focused on the *outflow* of employees from established firms to founders of new ventures (Agarwal et al., 2004; Franco and Filson, 2006; Gompers et al., 2005; Kacperczyk and Marx, 2016; Klepper and Sleeper, 2005; Sørensen and Fassiotto, 2011; Sørensen, 2007). We contribute to this research by providing a theoretical framework for the reverse process—namely the *inflow* of former founders to established firms as wage employees. In particular, we provide theoretical insights regarding how hiring firms evaluate founder experience during the initial stage of the hiring process, and how the evaluation varies by the venture's outcome—namely, venture failure versus success. Developing strong human capital through recruiting new hires is central to organizational performance (Baron, 2004; Beckman and Burton, 2008; Bidwell, 2011; Bidwell and Keller, 2014; Chadwick and Dabu, 2009; Molloy and Barney, 2015), and our study helps us understand how entrepreneurial human capital—which is important in promoting innovation and entrepreneurial culture in organizations—is evaluated by hiring firms.

Most importantly, our study builds on the organizational spawning literature by focusing on the evaluation of entrepreneurial success and failure. While recent studies have started to investigate how firms manage the *inflow* of entrepreneurial human capital, there has been mixed empirical evidence and competing explanations, making it difficult to understand how hiring firms assess former founders. Specifically, these inconsistent findings have blurred our understanding of whether organizational hiring strategies tend to prioritize signals of quality or of fit and commitment stemming from founder experience for job applicants, as summarized in the column headers of the matrix in Figure 3.1. Generally, we show that prior founders are disadvantaged in attempts to re-enter wage employment, which aligns with perspectives that founder experience is negatively evaluated on average. Importantly, our findings that venture success, which conveys positive signals related to superior capability and human capital (versus venture failure), magnifies this founder disadvantage challenges the notion that signals related to quality are the driving force in hiring in our context. As such, considering entrepreneurial success and failure is important to understand alternative theoretical perspectives on the transition from entrepreneurship to wage employment.

Insights from this study therefore contribute to two previously disparate streams of research related to organizational perspectives on entrepreneurial human capital.

First, our study has implications for research on entrepreneurship and information asymmetry (Anton and Yao, 1995; Hegde and Tumlinson, 2021; Mahieu et al., 2019). Based on the existing literature, we may expect successful founders to be preferred over failed founders, as venture success serves as a signal for superior capabilities and human capital as compared to venture failure, and thus reduces uncertainty about candidate quality. Yet, our study demonstrates that information about capabilities alone does not fully explain the hiring decision. For instance, Mahieu et al. (2019) attribute the wage discount suffered by Belgian former entrepreneurs to high uncertainty related to a former founder's capability or expected productivity. In fact, we find evidence that employers do not prefer former founders who experienced success and who may bring extraordinary capabilities into their firms, indicating that mechanisms related to quality are not the key mechanisms driving evaluations of former founders in the initial stage of hiring in our context.

Further, we contribute to research that examines the importance of fit and commitment in organizations. We bring theories of fit and commitment to understand organizational processes and structures that could affect the evaluation of former founders. We theorized that founder experience conveys a complex signal, not just related to a job candidate's quality, but also related to a job candidate's fit and commitment, which organizational scholars have established are important hiring considerations (Galperin et al., 2019; Goldberg et al., 2016; Leung, 2014; Rivera, 2012). Specifically, while the quality signal from entrepreneurial success may be beneficial, in our context it did not outweigh the negative signals related to fit and commitment of successful entrepreneurship. Our paper demonstrates that when firms evaluate founder experience, organizational concerns related to fit and commitment loom larger than perceptions related to quality.

Our results on the moderating effect of hiring firm age also engage with the debate in organizations research regarding the relationship between bureaucracy and entrepreneurial human capital (Kacperczyk and Marx, 2016; Sørensen and Fassiotto, 2011; Sørensen and Phillips, 2011; Sørensen, 2007; Sørensen and Stuart, 2000). Evidence from our study—that founder disadvantage is less pronounced among younger hiring firms—offers evidence that less bureaucratic firms are less likely to penalize former founders. The significant difference in the evaluation of successful former founders between younger and older firms further validates that our proposed fit and commitment mechanism is most pronounced for older, and thus likely more bureaucratic, organizations. This finding highlights the significant role of bureaucracy not only in the outflow of human capital to entrepreneurial ventures but also in the inflow of former founders to established firms.

Our research also contributes to the growing body of work about entrepreneurship and labor markets (Campbell et al., 2012; Levine and Rubinstein, 2017; Luzzi and Sasson, 2016; Mahieu et al., 2019; Manso, 2016; Sorenson et al., 2020). Although the findings from this prior research have been mixed, it has provided a key set of plausible mechanisms that may lead to a wage premium or discount for former founders, as well as former employees of startups. It is inherently difficult to control for supply-side mechanisms (e.g., selection by job candidates) and thus distinguish the mechanisms driving the demand-side evaluation (e.g., evaluation by hiring firms) with archival data of realized hires. By leveraging a field experiment design, we can hold supply-side mechanisms constant and focus our theorizing on the demand-side mechanisms affecting the evaluation of candidates with founder experience. For example, Manso (2016) proposes a supply-side explanation "learning through experimentation" to support his finding from longitudinal data that entrepreneurs prone to failure limit their wage loss by selecting into wage employment. We shed light on the demand-side mechanism: That hiring firms evaluate venture failure as a positive signal for fit and commitment relative to venture success, but that all founder experience is evaluated more negatively than non-founder experience. Moreover, Campbell (2013) and Luzzi and Sasson (2016) propose that mechanisms related to superior capability and human capital could lead to a wage premium for former founders. Our study contributes to this work by highlighting that mechanisms related to fit and commitment play a more significant role at the earlier stage of the hiring (interviews) in our context; thus, it is critical to consider the stage of the evaluation process when discussing mechanisms. As we contribute to the existing literature by focusing on the demand-side mechanisms, future research can further clarify the mechanisms driving the supply-side factors. Similarly, future work can focus on how the mechanisms affecting demand-side evaluation may change in later stages of the hiring process.

Finally, a theme of sociological research on careers has been on the various factors that affect an individual's career progression both within (Barnett et al., 2000; Baron and Bielby, 1980; Castilla, 2008; Goldberg et al., 2016) and across firms (Baron, 1984; Bidwell and Briscoe, 2010; Bidwell and Mollick, 2015; Cohen et al., 1998; Rider and Negro, 2015; Sørensen, 1977). The popularity of entrepreneurship as a career choice has resulted in the inclusion of entrepreneurship in this discussion, with an almost exclusive focus on the organizational spawning process. Our study begins to answer a call from researchers for a more comprehensive understanding of careers by considering entrepreneurship not as a final destination but as a "step along a career trajectory" (Burton et al., 2016, p. 237). Specifically, we develop theory and provide evidence for the implications of transitioning from entrepreneurship into established organizations. This research also informs how founder experience signals distinctive qualities about the candidate to hiring firms. There is much room for future research to continue to broaden our understanding of how founder experience fits into an individual's broader career path, such as whether this allows for switching one's career focus or how other previous experiences and other signals interact with founder experience when trying to enter the traditional labor market.

3.7.1 Generalizability

An inherent limitation of field experiments relates to the generalizability of results beyond the context. Thus, it is important to discuss how the key design choices related to the experiment may affect the interpretation of our results.

It is plausible that our estimated effects vary across types of entrepreneurs in a few key ways. First, our focus on individuals with a technical background may understate the level of disadvantage faced by former founders with other backgrounds. For example, in our post-experiment interviews, each recruiter had familiarity with early-career former founders in the recruiting process. In settings where applicants with founder experience would be seen as highly atypical (e.g., non-innovation related fields), former founders may receive a more negative evaluation. Specifically, a lack of familiarity with founder experience should magnify concerns related to fit and commitment.

Second, we focus on early-career founders. While we have discussed why this is the appropriate sample for theoretical, empirical, and policy considerations, it is important to address how this design choice affects the interpretation of our results. Focusing on early-career individuals may magnify the founder disadvantage as they have shorter career histories and lack previous affiliations that can assuage the hiring firm's concerns. Later-career founders can more easily use their previous work experience to show their ability to fit into and remain committed to a hiring firm. Conversely, a transition to entrepreneurship later in one's career may send a more negative signal. It could be seen as a very purposeful career pivot, and thus magnify concerns about fit and commitment. Exploring the evaluation of founder experience for later-career individuals remains an exciting path for future research.

Third, our application process took place online, which may also suggest a scope condition to our study. While this is the most frequent mode of job searching among early-career individuals applying for technical roles, as described by our pre-study informants and consistent with our post-experiment interviewees, we cannot speak to the effect of referrals in the evaluation of former founders, or alternative job search strategies. It may be the case that a referral will mitigate these concerns by vouching for the candidate in question, however, it may also be plausible that gaining a referral will be challenging, as the referrer may hold similar concerns about how their referral will affect their own reputation at their firm (cf. Smith, 2005).

3.7.2 Conclusions and Implications

Increasingly, firms have been claiming a desire for their employees to be more innovative and entrepreneurial (e.g., AT&T, 2018; Bendes, 2018; Ishak, 2017), with firms adopting executive positions to increase innovation and even creating innovation hubs/centers. However, we find evidence that former founders have a substantively lower callback rate than non-founders, especially from older firms. We believe this inconsistency between the espoused ideals and the reality of demonstrated hiring decisions stems from distinct signals associated with founder experience to different members of hiring firms, namely executives and recruiters. Claims about valuing entrepreneurial and innovative employees originate with organizational leaders and executives, but decisions on which applicants will be included for further consideration for a job are made by recruiters. Unlike executives, who are motivated to nurture entrepreneurial environments and are focused on long-term strategic initiatives, recruiters are motivated to evaluate candidates regarding their current quality, fit, and commitment. This is because these factors are related to worker retention (Goldberg et al., 2016; O'Reilly III et al., 1991), which is a key performance metric recruiters are evaluated against (Galperin et al., 2019; Leung, 2014; ?). Therefore, recruiters may not be motivated to bring in an entrepreneur if it is at the expense of affecting their own performance outcomes. Our results suggest that firms would benefit from clarifying their human capital strategy to the gatekeepers enacting this strategy—

recruiters—to better achieve the desired long-term human capital outcomes.

For policymakers, there is a significant focus on early-career entrepreneurs. Although the average entrepreneur may be more advanced in their career, recent policy demonstrates an effort to promote and provide resources for young entrepreneurs. In the U.S., the number of university courses in entrepreneurship has grown 20 times from 250 in 1985 to over 5,000 in 2008 (Kauffman Foundation, 2013), and the number of states that have K-12 standards for entrepreneurship education has more than doubled from 19 in 2009 to 42 in 2015 (Marich, 2015). Our research will help better inform well-rounded and transparent policy decisions in this area.

For current and aspiring entrepreneurs, our research provides insights into how to navigate the labor market after founder experience. For many individuals, entrepreneurship is not a destination point in their career but a step along their career path. While the lower callback rate for former founders may initially sound discouraging, we caution against an oversimplification in interpreting our results. It could be thought that entrepreneurship should be avoided by early-career individuals; however, we do not believe this to be the case. As mentioned above, firms have been increasingly looking for entrepreneurial and innovative talent, and the callback rate of 13.6 percent for former founders suggests that some hiring firms may value the human capital and entrepreneurial traits associated with founder experience. Instead, our findings highlight that founder experience carries a complex signal from the perspective of hiring firms, in particular recruiters, and thus former founders must update their labor market strategy accordingly. For example, early-career former founders should consider ways to offset potential concerns about their fit and commitment. Most importantly, founders—especially former successful founders—should focus on ways to emphasize their ability to fit into and remain committed to the hiring firm, and understand that certain firms, such as younger firms, should more highly value this experience.

3.8 Figures and Tables

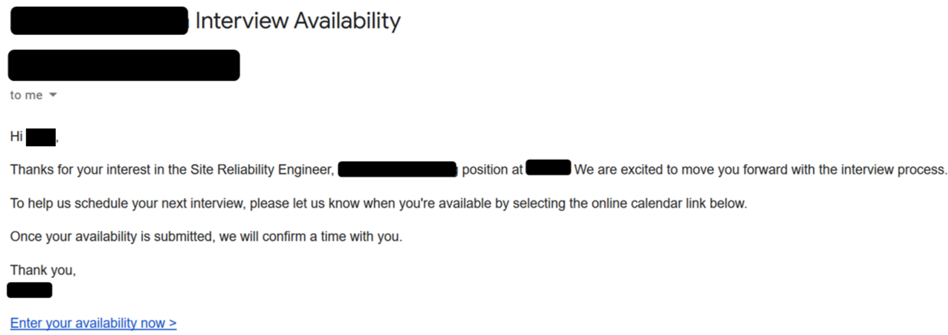
Figure 3.1: Theoretical Mechanisms for the Likelihood of Former Founders Receiving a Positive Evaluation From Hiring Firms by Venture Outcome

EFFECT OF FOUNDER EXPERIENCE	
INCREASE IN LIKELIHOOD	**DECREASE IN LIKELIHOOD**
• Capabilities, human capital, and entrepreneurial traits • Alignment with firm focus on innovation and entrepreneurial culture	• Information asymmetry about quality (i.e., capabilities, human capital) • Concerns about fit and commitment

VENTURE OUTCOME		
SUCCESS	**Q1. Venture Success Attenuates Concerns About Quality** • Successful former founders are more likely to be perceived as having higher quality (i.e., capabilities and human capital) • Successful former founders are more likely to be perceived as possessing more entrepreneurial and innovative skill sets • Successful former founders earn a premium in subsequent wage employment	**Q2. Venture Success Magnifies Concerns About Fit and Commitment** • Successful former founders are more likely to be perceived as having a lower fit with and commitment to hiring firms • Successful former founders are more likely to found another venture • Successful former founders are more likely to entice other employees to join them in entrepreneurship
FAILURE	**Q3. Venture Failure Attenuates Concerns About Fit and Commitment** • Failed former founders are more likely to be perceived as having a higher fit with and remain committed to hiring firms • Failed former founders are more likely to abandon entrepreneurship and find a better fit with wage employment • Failed former founders are less likely to poach other employees	**Q4. Venture Failure Magnifies Concerns About Quality** • Failed former founders are more likely to be perceived as having lower quality (i.e., capabilities and human capital) • Failed former founders are more likely to be perceived as coming from the lower tail of the quality distribution (or pushed into entrepreneurship) • Failed former founders may suffer status loss and lose bargaining power in the labor market

Notes: The column header of the matrix lists the mechanisms driving an increase (left column) and decrease (right column) in the likelihood former founders receiving a positive evaluation by hiring firms. Each quadrant in the matrix ("Q1" to "Q4") disentangles how these mechanisms would be strengthened or weakened based on a hiring firm's knowledge of the venture's outcome: success (top row) and failure (bottom row). For example, Q2 (top right) in the matrix discusses the mechanisms that would lead to a decrease in the likelihood that former successful founders receive a positive evaluation by hiring firms.

Figure 3.2: Callback Example



[redacted] Interview Availability

[redacted]

to me

Hi [redacted],

Thanks for your interest in the Site Reliability Engineer, [redacted] position at [redacted] We are excited to move you forward with the interview process.

To help us schedule your next interview, please let us know when you're available by selecting the online calendar link below.

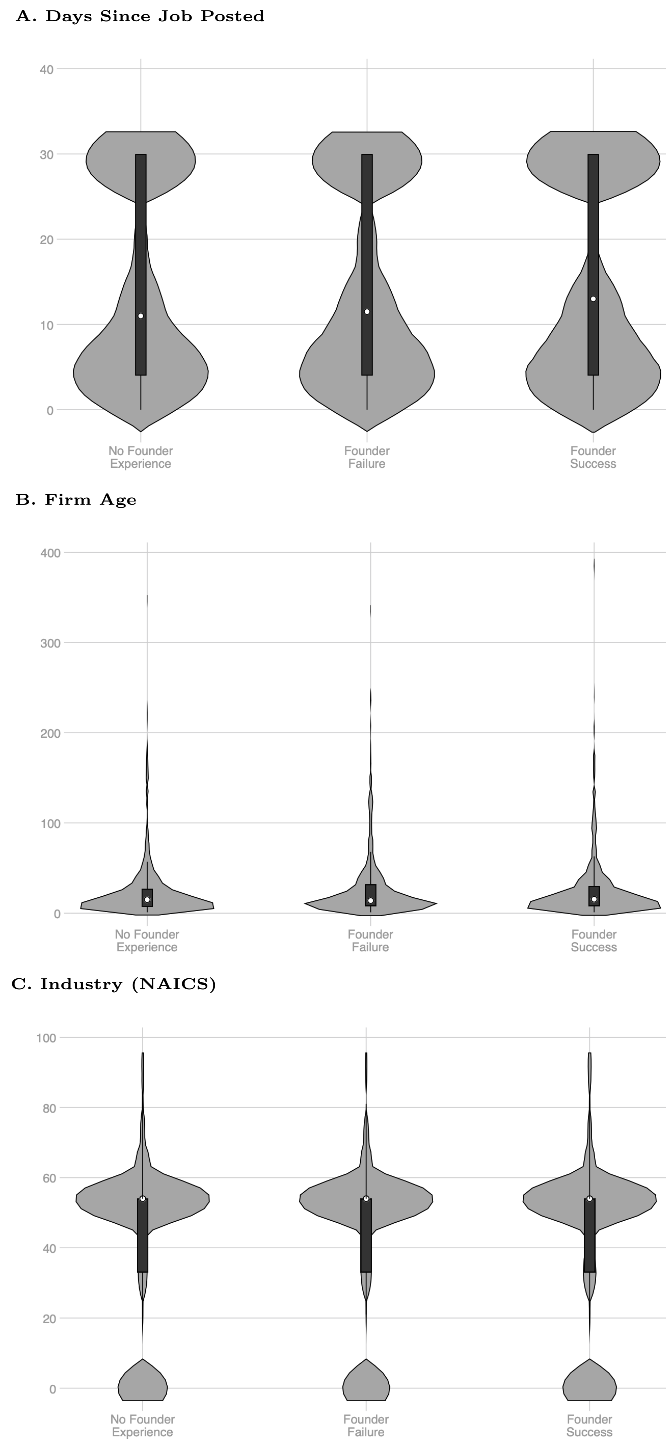
Once your availability is submitted, we will confirm a time with you.

Thank you,
[redacted]

Enter your availability now >

Notes: This is a random example of a request for interview (or callback) from a hiring firm.

Figure 3.3: Randomization Integrity

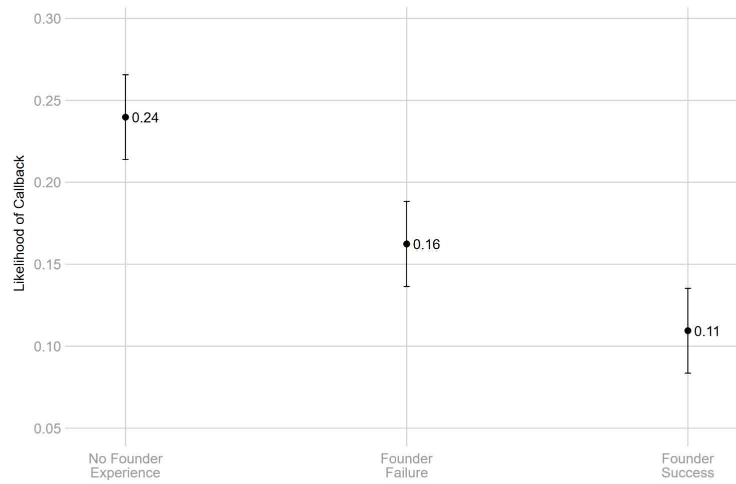


Notes: Each marker indicates the statistic's median, each box indicates the interquartile range, and spikes extend to the upper- and lower-adjacent values, as in a standard box plot. Overlaid with the box plot is the estimated kernel density, allowing us to better understand the distribution in each variable across the conditions

Figure 3.4: Founder Experience and Receiving a Callback: Non-Founders Versus Founders

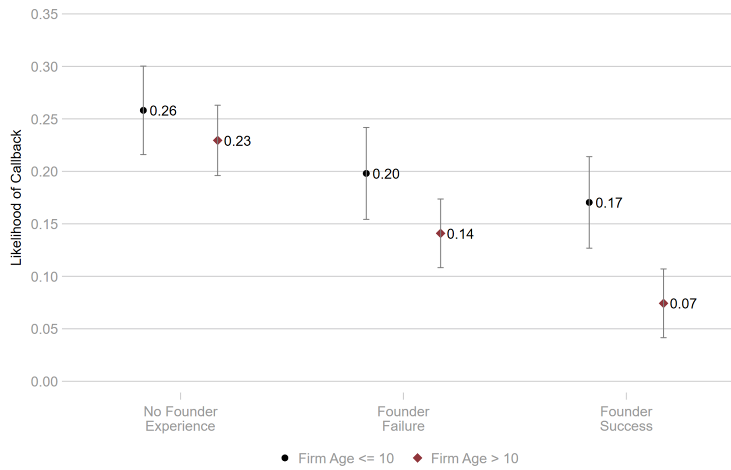
Notes: The figure shows the margin plot from regressing the likelihood of a Callback on the job applicant's founder experience, grouping failed and successful entrepreneurs (Table 3.5, Model 1B). The model includes controls for gender of the applicant, the number of days since the job was posted, the age of the firm being applied to, the posted city of the job opening, and the industry of the hiring firm. Bars represent 95 percent confidence intervals.

Figure 3.5: Founder Experience and Receiving a Callback: Failed Versus Successful Founders



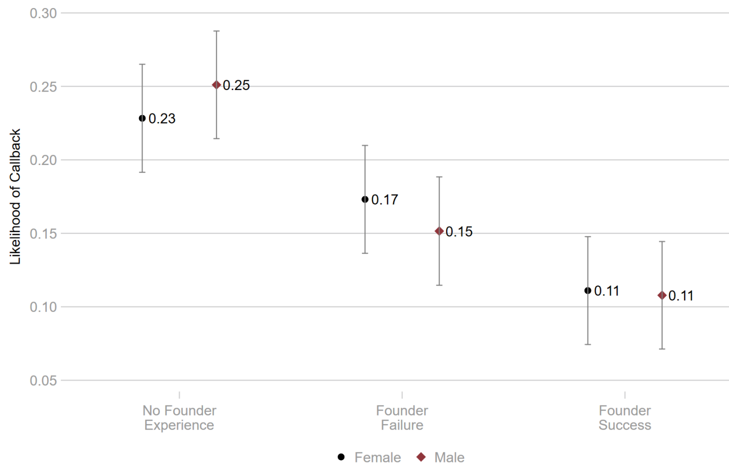
Notes: The figure shows the margin plot from regressing the likelihood of a Callback on the job applicant's founder experience (Table 3.6, Model 2B). The model includes controls for gender of the applicant, the number of days since the job was posted, the age of the firm being applied to, the posted city of the job opening, and the industry of the hiring firm. Bars represent 95 percent confidence intervals.

Figure 3.6: Founder Experience and Receiving a Callback: Young Versus Older Firms



Notes: The figure shows the margin plot from regressing the likelihood of a Callback on the job applicant's founder experience interacted with firm age (Table 3.7, Model 3B). In this regression firm age is a dichotomous variable indicating whether the firm was founded 10 or less years ago (as of the end of 2018). The model includes controls for gender of the applicant, the number of days since the job was posted, the posted city of the job opening, and the industry of the hiring firm. Bars represent 95 percent confidence intervals.

Figure 3.7: Founder Experience and Receiving a Callback: Female Versus Male Applicants



Notes: The figure shows the margin plot from regressing the likelihood of a Callback on the job applicant's founder experience interacted with *Female*. The model includes controls for the number of days since the job was posted, the age of the firm being applied to, the posted city of the job opening, and the industry of the firm being applied to. Bars represent 95 percent confidence intervals.

Table 3.1: Summary of Baseline Resume

Work Experience
• 3 years of full-time work experience
• Lead developer of the application
Education
• B.S. in Computer Science; graduated in 2015
• Undergraduate Researcher in Computer Science
• Board Member, Entrepreneur and Venture Club
Skills & Interests
• Python, Java, JavaScript, C/C++, AWS, Hadoop, SQL, Linux, JQuery
• Enjoy cooking, cycling, and traveling

Notes: On the actual resumes, each of these experiences and skills was described in detail with additional bullet points. The actual resumes were drafted in a typical resume format.

Table 3.2: Distribution of Submitted Applications by Experimental Conditions and Metropolitan Area

	No Founder Experience	Founder Failure	Founder Success	**City Total**	***City's Share***
Austin, TX	80	80	80	**240**	***0.100***
Boston, MA	147	147	146	**440**	***0.183***
Chicago, IL	116	116	117	**349**	***0.145***
Los Angeles, CA	101	102	102	**305**	***0.127***
New York, NY	180	180	180	**540**	***0.225***
San Francisco, CA	176	175	175	**526**	***0.219***
Total	**800**	**800**	**800**	**2,400**	***1.000***

Table 3.3: Descriptive Statistics

	N	Mean	SD	Min	Max
Callback	2,400	0.17	0.38	0.00	1.00
Days Since Job Posted	2,400	15.08	11.23	0.00	30.00
Firm Age[a]	2,369	26.92	36.95	1.00	389.00
Days to Callback[b]	411	8.99	10.67	0.00	59.00

[a]Founding year could not be found for 31 firms.
[b]Conditional on receiving a callback.

Table 3.4: Randomization Integrity

	No Founder Experience			Founder Failure			Founder Success		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
Days Since Job Posted	800	14.96	11.25	800	14.87	11.08	800	15.41	11.38
Firm Age[a]	792	25.61	35.06	785	28.24	38.08	792	26.91	37.65

Notes: T-Tests of Days Since Job Posted and Firm Age across conditions show that there are no statistical differences between any pair of conditions ($p < 0.05$). A chi-squared test confirmed that were no significant differences in the distribution of industry across conditions. These statistics do not include missing values.
[a]Founding year could not be found for 31 firms.

Table 3.5: OLS Regressions of Receiving a Callback on Founder Experience

	Model 1A	Model 1B
Founder	-0.10***	-0.10***
	(0.02)	(0.02)
Female		0.00
		(0.02)
Firm Age		-0.00*
		(0.00)
Days Since Job Posted		-0.00
		(0.00)
Location: BOS		0.02
		(0.03)
Location: CHI		-0.07*
		(0.03)
Location: LA		-0.05
		(0.03)
Location: NYC		-0.05^{+}
		(0.03)
Location: SF		-0.01
		(0.03)
Constant	0.24***	0.27***
	(0.01)	(0.03)
R-Squared	0.016	0.027
Observations	2,400	2,369

Notes: $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. *Founder* is a dichotomous variable that takes the value of 1 if the applicant was a founder and pools together both founder conditions (failure and success). Model 1B includes industry fixed effects. Firm age could not be found for 31 firms; for these observations we treated as missing values. *Location: AUS* is the reference category for dummy variables indicating geographic location of the firms. Standard errors in parentheses.

Table 3.6: OLS Regressions of Receiving a Callback on Founder Experience: Failed Versus Successful Founders

	Model 2A	Model 2B
Founder Failure	-0.08***	-0.08***
	(0.02)	(0.02)
Founder Success	-0.13***	-0.13***
	(0.02)	(0.02)
Female		0.00
		(0.02)
Firm Age		-0.00*
		(0.00)
Days Since Job Posted		-0.00
		(0.00)
Location: BOS		0.02
		(0.03)
Location: CHI		-0.07*
		(0.03)
Location: LA		-0.05
		(0.03)
Location: NYC		-0.05^{+}
		(0.03)
Location: SF		-0.01
		(0.03)
Constant	0.24***	0.27***
	(0.01)	(0.03)
R-Squared	0.020	0.030
Observations	2,400	2,369

Notes: $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. *Founder Failure* is a dichotomous variable that takes the value of 1 if the applicant was a founder that failed, *Founder Success* is a dichotomous variable that takes the value 1 if the applicant was a founder that succeeded, and the reference category are applicants with no founder experience. Model 2B includes industry fixed effects. Firm age could not be found for 31 firms; for these observations we treated as missing values. *Location: AUS* is the reference category for dummy variables indicating geographic location of the firms. Standard errors in parentheses.

Table 3.7: OLS Regressions of Receiving a Callback on Founder Experience: Younger Versus Older Firms

	Model 3A	Model 3B
Founder Failure	-0.09***	-0.09***
	(0.02)	(0.02)
Founder Success	-0.16***	-0.16***
	(0.02)	(0.02)
Firm Age (less than 10)	0.02	0.03
	(0.03)	(0.03)
Founder Failure × Firm Age (less than 10)	0.03	0.03
	(0.04)	(0.04)
Founder Success × Firm Age (less than 10)	0.07^{+}	0.07^{+}
	(0.04)	(0.04)
Female		0.00
		(0.02)
Days Since Job Posted		-0.00
		(0.00)
Location: BOS		0.02
		(0.03)
Location: CHI		-0.07*
		(0.03)
Location: LA		-0.05
		(0.03)
Location: NYC		-0.05^{+}
		(0.03)
Location: SF		-0.02
		(0.03)
Constant	0.23***	0.24***
	(0.02)	(0.04)
R-Squared	0.026	0.033
Observations	2,369	2,369

Notes: $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. *Founder Failure* is a dichotomous variable that takes the value of 1 if the applicant was a founder that failed, *Founder Success* is a dichotomous variable that takes the value 1 if the applicant was a founder that succeeded, and the reference category are applicants with no founder experience. *Firm Age (less than 10)* is a dichotomous variable that takes the value of 1 if the firm being applied to is 10 years old or younger (as of the end of 2018). Model 3B includes industry fixed effects. Firm age could not be found for 31 firms; for these observations we treated as missing values. *Location: AUS* is the reference category for dummy variables indicating geographic location of the firms. Standard errors in parentheses.

Table 3.8: Interviewee Information

	Recruiter			Firm		
Recruiter	Years of Experience	Gender	Location	Industry	Age	Type
1	5-10	Male	NYC	Healthcare Tech	5-10	Private
2	5-10	Female	NYC / SF	Technology / Media	10-15 / 30-50	Private / Public
3	10-15	Male	NYC	Technology	20-25	Public
4	3-5	Male	SF	Technology	10-15	Public
5	5-10	Male	NYC	Finance	15-20	Private
6	5-10	Male	NYC	Finance	15-20	Private
7	3-5	Female	CHI / AUS / LA	Finance / Technology	20-30 / 20-30	Private / Public
8	15-20	Female	BOS	Healthcare Tech	50-75	Public
9	15-20	Female	BOS	Technology	50-75	Public
10	20-25	Female	AUS	Technology	5-10	Private (VC)
11	1-3	Male	LA / SF	Tech Recruiting	10-15	Private
12	1-3	Female	LA	Tech Recruiting / Technology	3-5 / 3-5	Private / Public
13	20-25	Female	LA	Technology	10-15	Private (VC)
14	3-5	Male	LA	Tech Recruiting	3-5	Private
15	3-5	Male	LA	Tech Recruiting	10-15	Private
16	10-15	Male	AUS	Technology	15-20	Private (VC)
17	5-10	Female	AUS / LA	Technology	5-10	Private (VC)
18	5-10	Female	SF / LA	Technology	15-20	Private (VC)
19	3-5	Male	CHI	Technology / Marketing	25-30	Private (VC)
20	3-5	Male	CHI / BOS	Technology / Platform	5-10	Private (VC)

Notes: Interviewee 2, 7, and 12 have recently worked at two different firms and spoke on their experiences at both places. For firm types, "VC" indicates whether a private firm has ever received venture capital funding.

3.9 Appendix of Chapter 3

In this appendix, we analyze whether the callback rates for each founder condition varies by gender of the applicant. Given the prevalent gender bias in other hiring audit studies (Rivera and Tilcsik, 2016) and broader implications of the findings, for each founder condition we created profiles and application materials for both female and male candidates. To signal gender of the job candidate, we varied the first name on the resume and cover letter.

The variable *Female* takes the value of 1 if the applicant's name is strongly associated with a woman and 0 if the applicant's name is strongly associated with a man. Figure 3.7 shows that employer preference using callback rates is not affected by an applicant's gender. The mean difference in callback rates for female and male applicants is not significantly different across conditions: 22.8 percent (female) versus 25.1 percent (male) in the non-founder experience condition, 17.3 percent (female) versus 15.2 percent (male) in the founder failure condition, and 11.1 percent (female) versus 10.8 percent (male) in founder success condition. Therefore, in this context, our evidence demonstrates that female and male applicants are evaluated similarly and have the same likelihood of receiving an initial callback from recruiters regardless of condition.

[Figure 3.7]

Initially, these gender results were surprising given the commonly found gender penalty across different settings, especially in male-dominated contexts such as STEM (Eagly and Karau, 2002; Lyness and Heilman, 2006; Zhang, 2020). Moreover, resulting from gender role incongruity (Kanter, 1977; Ridgeway, 1997; Wagner and Berger, 1997), female entrepreneurs have been found to be disadvantaged when evaluated by external resource providers (Abraham, 2019; Lee and Huang, 2018).

One reason for a lack of gender difference in our results may be due to the high demand for those with software engineering skills in the U.S. economy (Kessler, 2017; Stansell, 2019). However, our post-experiment interviews offer an additional explanation related to recent diversity and inclusion efforts. Specifically, our interviewees (listed in Table 3.8) highlighted how these efforts may not be working as intended. Many recruiters mentioned that their firm had a team dedicated to diversity and inclusion initiatives and that they prioritize giving more opportunities to women and people of color. Recruiter 11, who works at a tech-focused search firm, described how his client firms are willing to pay a premium to recruit "women in tech" and asking him to pass along as many profiles of female engineers that he has: "Clients are specifically looking for women and minorities. There's a huge pay gap in favor of women. Clients specifically request "I either want a woman or a black person." This evidence helps to contextualize the lack of gender difference in the callback rate during the initial stage of the hiring process. However, it is less clear if this is leading to more women being hired. While outside of the scope of this study, Recruiter 2, stated that 2 out of her last 10 later-round interviews were with women. A technical recruiter at a search firm (Recruiter 16) who noted that "tons of companies come to us because all they want is diversity candidates" also stated that his clients are interviewing a lot of diversity candidates but not hiring them at the same rate.

Overall, our field experiment results are encouraging regarding initial parity in callback rates, however, our conversations with recruiters suggest that delving further into whether these results indicate equality or a forced curve is important. Furthermore, it is unclear how female candidates for these positions are evaluated during the later stages of the hiring process. Supporting this lack of progress, industry reports show that these diversity and inclusion efforts are falling short and that concrete improvements have not yet been made (Conway et al., 2018; Shaikh et al., 2018). Therefore, our research highlights the importance of considering outcomes in relation to the stage of the evaluation being analyzed.

Chapter 4

Democratizing Startup Investing: Game Changer or Empty Promise for Inclusive Entrepreneurship?

4.1 Introduction

Financial capital shapes the survival and evolution of early-stage businesses, but not all entrepreneurs have equal access to this capital (Hwang et al., 2019). Fewer than 15 percent of new businesses that hire in the U.S. receive capital from institutions (e.g., venture capital, bank loans),[1] with most relying on personal savings and credit cards. Whether a startup can mobilize resources from institutions varies by the human capital and demographic characteristics of entrepreneurs (Beckman et al., 2007; Hegde and Tumlinson, 2014; Shane and Stuart, 2002; Sorenson and Stuart, 2008). A small group of entrepreneurs funded by angel investors and venture capitalists (VCs) often mirror the characteristics of the professional investors, who also do not come from diverse backgrounds. Both groups are predominantly White, male, located in tech-

[1] https://www.census.gov/programs-surveys/ase.html

nology hubs and graduates of elite universities (Deloitte and Venture Forward, 2021; Huang et al., 2017; Rider, 2012). Entrepreneurs outside these groups face challenges in mobilizing financial resources.

To address these barriers in capital access, entrepreneurs and policymakers across countries have advocated for equity crowdfunding, which allows the general public to invest in startups in exchange for their securities. The new form of startup financing has the potential to democratize the funding process by broadening the pool of prospective investors and making them equally accessible to any entrepreneurs via online platforms.[2] In the U.S., Regulation Crowdfunding, implemented in May 2016, has allowed startups to acquire capital from a crowd of non-accredited investors ("crowd investors" or "the crowd"). Regulation Crowdfunding ("equity crowdfunding") is the enactment of Title III of the Jumpstart Our Business Startups (JOBS) Act, which was passed in 2012 to encourage the funding of startups and small businesses. Some industry experts and high authorities, including former President Obama who called the act a "potential game changer," consider equity crowdfunding as a promising solution to help entrepreneurs overlooked by professional investors. However, others cast doubt on whether it could overcome the shortcomings of traditional sources of capital (Andersen, 2013; Mims, 2015; Stanford, 2020). If crowds prefer the same types of startups and entrepreneurs as professional investors, funding disparities would persist. I therefore ask: *Does allowing the general public to invest in startups democratize capital access by supporting underrepresented entrepreneurs?*

The existing literature also points to competing predictions. Sociological perspectives on resource exchange suggest that equity crowdfunding can remove struc-

[2] The differences between equity crowdfunding and other forms of crowdfunding, including reward-based crowdfunding (e.g., Kickstarter projects), are discussed in the Empirical Context section. In essence, the other forms do not allow an individual to purchase securities of participating firms and become their shareholders. Equity crowdfunding is characterized by more capital at stake, risk and uncertainty, in exchange for a high potential upside. The deal terms, investment size, time horizon, and risks involved are more akin to angel investors and VCs' funding, rather than the other forms of crowdfunding.

tural barriers faced by underrepresented entrepreneurs. Mobilizing resources from the crowd allows entrepreneurs to access investors on online platforms, thereby reducing the need for pre-existing relationships with investors (Canales and Greenberg, 2016; Hegde and Tumlinson, 2014; Hochberg et al., 2007; Rider, 2012; Sorenson and Stuart, 2001; Stuart and Ding, 2006; Thébaud, 2015). Similarly, homophily, which explains the tendency to form relationships with others based on shared characteristics (Ertug et al., 2021; Greenberg and Mollick, 2017; Kleinbaum et al., 2013; McPherson et al., 2001), could help underrepresented entrepreneurs receive support from crowd investors, if the crowd comes from more diverse backgrounds than professional investors.[3]

However, research on collective evaluations suggests that investment decisions by crowd investors may not look so different from those of professional investors. To assess the quality of ideas and products, crowds and experts attend to similar evaluation criteria and heuristics (Mollick and Nanda, 2016; Younkin and Kuppuswamy, 2018). Past studies have mostly examined evaluations by crowds and experts in reward-based crowdfunding activities, involving the backing of creative projects, but even greater information asymmetries exist when assessing the quality of entrepreneurs and startups (Anton and Yao, 1995; Botelho and Chang, 2022; Hegde and Tumlinson, 2021; Hsu and Ziedonis, 2013). To reduce these uncertainties, equity crowd investors may rely on the same quality signals, such as funding history and founding team backgrounds, as professional investors (Huang and Pearce, 2015; Scott et al., 2020). Furthermore, if crowd investors make their own decisions based on the evaluations of professional investors—by referring to funding status and discussion boards on online platforms—crowds will reinforce, rather than correct, existing biases and prevalent views held by others (Botelho, 2017; Salganik et al., 2006). This new form

[3]The background and composition of crowd investors remain unknown. The personal information about investors collected by platforms or issuing firms cannot be disclosed under privacy laws including Regulation S-P (Privacy of Consumer Financial Information and Safeguarding Personal Information).

of mobilizing capital would then still leave behind underrepresented entrepreneurs.

To test these competing accounts, I used (1) hand-collected data on the universe of startups that participated in Regulation Crowdfunding ("ECF firms") and (2) data on startups—of similar stages and businesses as ECF firms—that had the opportunity but did not crowdfund ("non-ECF firms"). Firms receive less capital from crowd compared to professional investors, on average, but have a greater chance of securing at least one investment by participating in equity crowdfunding. To investigate whether equity crowdfunding has altered the *direction* of funding beyond increasing the *rate* of funding, I examined the similarities and differences in firm and founding team characteristics funded by crowd and professional investors. This analysis reveals three interesting patterns. First, crowd investors, like professional investors, attend to evidence of quality (i.e., prior funding history). Second, equity crowdfunding has provided more equitable capital access for entrepreneurs underrepresented in terms of educational and professional background, location, and industry. Having past founder experience or holding a degree from an elite university strongly impacts the funding decisions of professional investors but not those of crowd investors. Firms engaging in industries less preferred by professional investors (i.e., non-high-technology sectors) and firms located in regions with fewer VC investments reap more benefits from equity crowdfunding, relative to those engaging in high-technology sectors and those located in regions with greater VC presence. Third, while firms with greater percentages of female, Black, and Hispanic founding members are more likely to choose equity crowdfunding over traditional sources of capital, crowd and professional investors fund these entrepreneurs at similarly low rates.

Overall, equity crowdfunding has improved capital access for certain groups of underrepresented entrepreneurs, but not all. Crowd investors can offer additional access to capital for entrepreneurs typically overlooked by professional investors for reasons related to embedded resource exchange dynamics (i.e., shared educational and professional backgrounds, region, and industry)—especially, those socially and spatially distant from professional investors. Yet the introduction of crowd investors has not ameliorated gender- and race-based disparities in startup financing. This research contributes to our knowledge on resource mobilization in entrepreneurship by demonstrating how equity crowdfunding has changed resource exchange dynamics between entrepreneurs and investors. It also builds on research examining the growing role of crowds in affecting organizational processes and outcomes by considering the implications on startup funding, which are important for venture survival and job creation. This study also contributes to scholarly and policy discussions on inequalities in entrepreneurship, and calls for more active interventions to reduce biases based on status characteristics, such as gender and race. A better understanding of how crowd investors, compared to professional investors, make startup investment decisions also has implications for policymakers, entrepreneurs, and investors.

4.2 Empirical Context: Regulation Crowdfunding in the U.S.

Equity crowdfunding allows startups and small businesses to mobilize resources from ordinary individuals by selling their securities. In the U.S., Regulation Crowdfunding, which prescribes the rules governing the offer and sales of securities to a crowd of non-accredited investors, was first introduced as part of the 2012 Jumpstart Our Business Startups (JOBS) Act and is regulated by the Securities and Exchange Commission ("SEC"). The act outlines rules to ease securities regulations related to the funding of small businesses, following a slowdown in startup activities in the wake of the 2008 financial crisis.

Specifically, Title III of the act allows firms to publicly sell up to \$1.07 million in equity per year to non-accredited investors. This regulation was formally enacted in 2015 with the first offering occurring on May 16, 2016.[4] Even after the adoption of the JOBS Act, policymakers have pushed for amendments to improve the equity crowdfunding framework. In particular, many entrepreneurs, especially those of growth-oriented or innovation-driven startups, considered the funding limit as inadequate to sustain their businesses. On May 2012, the SEC has increased the limit to $5 million per year.

Compared to traditional sources of startup financing provided by commercial lenders, angel investors, and VCs, equity crowdfunding has the potential to broaden the scope of investors and entrepreneurs that participate in the capital markets. From the startup resource demand side, entrepreneurs, regardless of their backgrounds, can engage with thousands of investors by creating a campaign page on one of the SEC-registered equity crowdfunding platforms (e.g., Wefunder, StartEngine). Previously, the majority of entrepreneurs without any mutual connections or shared affiliations with professional investors had scant likelihood of scheduling a meeting and pitching venture ideas. Banks and financial institutions also have limits on the eligibility of borrowers and loan sizes for small businesses, increasing the difficulty for entrepreneurs without track records. From the resource supply side, any individuals over 18-years-old can invest a relatively small amount of money, as little as $100, in a startup. They can invest up to $2,200 a year in all Regulation Crowdfunding offerings, with this investment limit growing with income and net worth.[5] The locus of decision-making regarding startup investments has shifted from a small pool of

[4]In this paper, I do not consider equity crowdfunding offerings in the form of Regulation A+ or Regulation D. Regulation A+ allows startups to raise up to $75 million from non-accredited investors, yet I focused my analysis on Regulation Crowdfunding because it covers a greater number of offerings and includes startups at earlier stages that face greater difficulties in accessing capital. Regulation D offerings are allowed to advertise and sell their securities online for unlimited funding amount, but investment in these securities are available only to "accredited investors," high-net-worth individuals or investment advisors, as determined by the SEC. As such, this form does not align with my definition of "democratizing" startup investing.

[5]Non-accredited investors are able to invest (i) the greater of $2,200 or 5 percent of the lesser of the investor's annual income or net worth if either amount is less than $107,000 or (ii) 10 percent of the lesser of the investor's annual income or net worth, up to $107,000, if both the annual income and net worth are equal to or greater than $107,000.

professional investors to a broader population of individuals interested in supporting new or growing enterprises and becoming shareholders of these firms.

Mobilizing resources from the crowd is not a new concept, and two pre-existing forms of crowdfunding—reward-based crowdfunding (e.g., Kickstarter, Indiegogo) and debt-based crowdfunding (e.g., Prosper, LendingClub)—have gained popularity over the past years. All of these forms of crowdfunding are common in terms of drawing on relatively small amounts of capital from a large number of individuals to fund projects or firms. However, equity crowdfunding differs from reward-based and debt-based crowdfunding (Agrawal et al., 2014; Bapna and Ganco, 2021) in four key ways. First, equity crowdfunding has the greatest ambiguity in terms of the form and value of return. Whereas resource providers of reward-based or debt-based crowdfunding have clarity in terms of promised returns (e.g., tickets to a theatrical production or advertised products for reward-based crowdfunding offerings; pre-defined interest and principal for debt-based crowdfunding offerings), investors of equity crowdfunding face ambiguities and uncertainties related to whether there will be any return and the value of the equity stake in a startup. Second, the total offering size and minimum contribution amount by each investor is more sizeable in equity crowdfunding (i.e., up to $1.07 million in a 12-month period with a typical minimum investment amount of $100). In comparison, the minimum investment amounts for reward-based and debt-based crowdfunding offerings outlined by the largest platforms in the U.S.—Kickstarter and LendingClub—are $1 and $25, respectively. Third, the time horizon for returns is explicit for reward-based or debt-based offerings and typically realized in less than five years. For most equity offerings, returns occur only in exit events such as an acquisition or an IPO. Lastly, the motivation to contribute to equity crowdfunding is mostly for financial returns, though it could also be partly driven by non-financial rewards, such as helping like-minded entrepreneurs solve important social issues. The motivation to contribute to reward-based crowdfunding is driven by nonpecuniary rewards (e.g., having creative input into a product in development, becoming early customers or having an opportunity to meet creators). In sum, equity crowdfunding is characterized by more capital at stake, risk and uncertainty, all in exchange for a higher potential upside. The deal terms, investment size, time horizon, and risks involved in equity crowdfunding are more similar to angel investors and VCs' funding, rather than reward-based or debt-based crowdfunding.

In addition to the composition of the investment pool, there are a few notable differences in mobilizing resources from crowd and professional investors, and I describe these differences in terms of drawbacks and benefits from the perspective of entrepreneurs. Equity crowdfunding involves unique costs related to level of disclosure, uncertainty in receiving a minimum amount of payment and campaign costs. Because equity crowdfunding offerings are open to the public, firms must disclose their milestones, business plans, terms of offerings and financial performance in statements submitted to the SEC; no such information disclosure requirements exist for private offerings involving professional investors. Equity crowdfunding in the U.S. operates under an "all-or-nothing" scheme, meaning that firms can collect the amount raised only if they meet minimum target amounts by the deadline date disclosed in the offering statement. For example, if a firm sets a minimum target amount of \$100,000 but has only received \$90,000 by the deadline date, then the offering has failed and the amount collected by the platform is returned to the investors.[6] Entrepreneurs who participate in equity crowdfunding incur costs related to platform fees and marketing expenses associated with crowdfunding campaigns, on top of legal and accounting expenses. Total costs related to a campaign are approximately 5.3 percent of the amount raised; however, the costs tend to be much lower than what a private offering

[6]Why, then, don't entrepreneurs establish low minimum targets to secure funding? Crowdfunding platforms and online forums advise entrepreneurs to establish the minimum targets equal to the lowest amount that would make the company viable. Companies are also required to report how they will use the proceeds in their filings to the SEC, so that investors can make informed decisions. Thus, establishing minimum targets lower than funding need may drive away investors.

from professional investors would cost in legal and accounting fees alone.[7]

In terms of unique benefits, equity crowdfunding increases exposure to a broader audience. A successful campaign can allow a firm to build an army of customers and brand ambassadors. While equity crowdfunding may not provide mentoring and advice from professional investors, who have more experience in guiding early-stage startups, it allows firms to get direct feedback and support from new and existing customers. Also, compared to professional investors who are incentivized to invest in startups strictly to generate financial returns, crowd investors, who invest relatively small amounts of money, often decide to invest in startups for nonpecuniary reasons, such as supporting a social cause or local small business owners.

Startups that participate in equity crowdfunding may be of lower quality and turn to crowd investment because they were unsuccessful in generating investment from professional investors. While there could be sorting of startups from the lower tail of the quality distribution, high-quality startups might also choose to participate in equity crowdfunding, for strategic reasons. Equity crowdfunding allows founders to increase exposure and credibility to customers, as well as to design attractive deal terms by establishing their own valuation and minimizing dilution of their equity stake without having to negotiate these terms with professional investors. In fact, 19% of Regulation Crowdfunding firms have previously raised funding from professional investors. More recently, equity crowdfunding platforms have started to form partnerships with leading accelerator programs (e.g., Wefunder with Y Combinator, Republic with 500 Startups) to showcase startups endorsed by professional investors. Thus, founders who choose to mobilize resources from crowds appear to come from the full range of the quality distribution.

As of March 2021, there have been a total of 3,568 offerings by 3,246 firms listed on 72 SEC-registered platforms. Entrepreneurs of 2,042 firms (2,305 offerings) have

[7] https://crowdfundcapitaladvisors.com/how-much-does-a-regulation-crowdfunding-campaign-actually-cost/

reached their minimum target amounts and successfully raised $672 million in total. The median and maximum amounts raised from successful offerings is $52,442 and $5 million; the median post-money valuations of these companies is $6.3 million. These amounts are compatible with the investment and valuation sizes of early-stage startups funded by angel investors, although they tend to be smaller than those of VCs.[8] The distributions of the amount raised from the successful offerings and valuation amounts can be found in Figures 4.1 and 4.2).

[Figure 4.1]

[Figure 4.2]

4.3 Theoretical Background

4.3.1 Resource Exchange and Social Influence in Entrepreneurship

Two social mechanisms related to resource exchange dynamics between entrepreneurs and investors—specifically, social capital and homophily—could explain why the introduction of crowd investors could remove structural constraints faced by underrepresented entrepreneurs.

Social networks constrain or promote economic and organizational activities (King, 2021; Stuart and Sorenson, 2007), especially in the context of entrepreneurship, which involves high levels of risks and uncertainties surrounding a newly established

[8] According to the Angel Capital Association's latest report, the median investment size for Seed and Series A rounds is $120,000 (Angel Capital Association, 2020). Based on Crunchbase database, the median investment size and post-money valuation of all companies with the same firm age and industry as startups that participate in equity crowdfunding are $2.0 million and $5.6 million, respectively. Based on VentureXpert database, the median investment size and post-money valuation of all VC investments in Seed and Early Stage companies between 2016 and 2020 are $5.2 million and $600 million, respectively.

firm (Freeman et al., 1983; Stinchcombe, 1965). To reduce these uncertainties, entrepreneurs and investors rely on their existing networks to source scarce information about business or investment opportunities (Canales and Greenberg, 2016; Hochberg et al., 2007; Renzulli et al., 2000; Shane and Stuart, 2002; Sorenson and Stuart, 2001; Stuart and Ding, 2006). In addition, social networks between entrepreneurs and investors convey trust, increase the reliability of the information about each other, and reduce the likelihood of malfeasance (Granovetter, 1985; Shane and Stuart, 2002). Therefore, entrepreneurs disadvantageously positioned in capital markets—in terms of educational and professional affiliations (Hsu, 2007; Rider, 2012; Shane and Stuart, 2002), gender (Guzman and Kacperczyk, 2019; Thébaud and Sharkey, 2015), race and ethnicity (Aldrich and Waldinger, 1990; Hegde and Tumlinson, 2014), and location (Sorenson and Stuart, 2001)—have been overlooked by professional investors. If entrepreneurs of advantaged and disadvantaged network positions are provided equal opportunities to access investors, there may be fewer disparities in capital access. Equity crowdfunding intends to introduce a firm to a large number of individuals via online intermediary platforms, potentially reducing the importance of pre-existing relationships or shared affiliations with a small circle of angel investors and VCs.[9]

Homophily, which explains the tendency to form relationships with others based on shared characteristics (Ertug et al., 2021; Kovacs and Kleinbaum, 2020; Lazarsfeld et al., 1954; McPherson et al., 2001), may also explain why equity crowdfunding could democratize capital access. This basis of attraction has led underrepresented entrepreneurs—who do not share social identities and affiliations with professional investors—to receive funding at much lower rates. For example, individuals favor

[9]Past studies focused on reward-based crowdfunding settings find that the social network size of individuals seeking funding is associated with crowdfunding success (Agrawal et al., 2011; Mollick, 2014). Yet the authors examine the social network of personal connections (e.g., number of Facebook friends) to understand the role of friends and family as early supporters, not the connections with professional investors. This evidence suggests that having more personal connections may still be important for gaining traction in crowdfunding, but the importance of relationships with professional investors is less clear.

business partners of the same gender who tend to have more similar interests and backgrounds (Ibarra, 1993; Kleinbaum et al., 2013). Since professional investors have been predominantly men—with reports revealing that only 14 percent of VC partners and 22 percent of angel investors are women (Deloitte and Venture Forward, 2021; Huang et al., 2017)—female-led ventures have received disproportionately less capital. Yet if a broadened pool of investors includes more diverse social backgrounds, then all entrepreneurs are more likely to share characteristics with crowd investors. Crowd investors from underrepresented groups in entrepreneurship might even exhibit homophilous behavior out of a desire to help others overcome structural barriers that they had faced (Bapna and Ganco, 2021; Greenberg and Mollick, 2017).

Taken together, these mechanisms suggest that equity crowdfunding could democratize capital access and support entrepreneurs historically underrepresented by professional investors. However, an important scope condition underlying these mechanisms is that crowd investors need to come from more diverse social groups than professional investors. If a large proportion of crowd investors consists of professional investors or if crowd investors resemble professional investors in terms of background and experience, equity crowdfunding may not help diversify investment in underrepresented entrepreneurs.

4.3.2 Startup Evaluations by Crowds and Experts

Despite the explanations that equity crowdfunding could reduce structural barriers, research on the wisdom of crowds and related work challenge the notion that it could democratize startup investing. Crowd investors may be attracted to the same set of startups as professional investors. If the "wise" crowd makes similar investment decisions as professional investors, the new form of mobilizing capital may not work as intended.

Assessing novel ideas and startup investment opportunities involves high levels of information imperfections and uncertainties (Anton and Yao, 1995; Botelho and Chang, 2022; Hegde and Tumlinson, 2021; Hsu and Ziedonis, 2013); even experienced professional investors face difficulty when evaluating startup investment opportunities (Hall and Lerner, 2010; Huang and Pearce, 2015; Scott et al., 2020). Professional investors have thus relied on various signals, including market and technology, as well as founding team background and experience (Gompers et al., 2020). For example, startups founded by entrepreneurs with prior founder experience or with advanced educations are more likely to receive VC funding (Beckman et al., 2007; Hsu, 2007). Professional investors also use heuristics and biases based on the demographic characteristics of founding members to make funding decisions. For example, female entrepreneurs and racial minorities tend to receive less funding, likely due to stereotypical assumptions that women do not possess entrepreneurial traits or that Black founders are of lower quality (Bapna and Ganco, 2021; Guzman and Kacperczyk, 2019; Kanze et al., 2018; Lee and Huang, 2018; Thébaud and Sharkey, 2015; Younkin and Kuppuswamy, 2018). Faced with even greater uncertainties and information imperfections given the relative lack of expertise and relationships with experts, crowd investors may rely on these signals even more, which could further disadvantage underrepresented entrepreneurs.

Although it is less clear how crowd investors evaluate startups, scholars have investigated similarities and differences in evaluations by crowds and professional experts in the context of reward-based crowdfunding. In one study, Mollick and Nanda (2016) find that the crowd is equally good at evaluating quality as experts and can make rational decisions based on available quality signals, such as the degree of formality in language and whether founders use videos and pictures in their campaigns. Another study finds that mobilizing resources from the crowd did not reduce discrimination against African American entrepreneurs, due to unconscious bias (Younkin and Kuppuswamy, 2018). These findings suggest that the crowd and experts use similar evaluation criteria and heuristics when making funding decisions. Equity crowdfunding, which may or may not generate investment returns, are characterized by higher risk and uncertainty compared to reward-based crowdfunding, which involves backing creative ideas or projects with a specific outcome and smaller contribution amount; as such, there may be greater alignment between the decisions of crowds and experts in equity crowdfunding compared to reward-based crowdfunding setting.

Relatedly, research on collective evaluations suggests that crowd investors may reinforce, rather than correct, biases and opinions held by other evaluators. Although crowd investors invest as individuals, that does not mean that their decisions are independent. Socially-influenced decisions often lead to reinforcement, rather than correction, of existing biases and prevalent views (Botelho, 2017; Salganik et al., 2006). One notable behavior is herding, wherein individuals allocate resources to subjects that have already received support from others (Kuppuswamy and Bayus, 2017). For example, a crowd investor may refer to funding status or discussion boards on crowdfunding platforms to assess others' opinions. This socially-influenced behavior can be more pronounced in response to endorsements by professional investors, who are of higher status in the startup investing space (Merton, 1968; **?**). Specifically, the crowd may look for startups which had previously received funding from professional investors or startups with campaign pages that show a professional investor participating in the crowdfunding offering. Reinforcing decisions made by professional investors, whose collective decisions demonstrate biases toward certain firm and founding team characteristics, could magnify disadvantages faced by underrepresented entrepreneurs.

The above mechanisms suggest similarities in startup evaluations by crowd investors and professional investors. However, the literature points to one caveat that could lead to differences in funding decisions between crowd and professional investors. Knowledge sourcing and decisions by crowds often outperform those by experts, because having a group with diverse experiences and preferences could reduce information frictions and biases held by experts, who often share homogeneous tastes and opinions (Baldwin and Von Hippel, 2011; Bayus, 2013; Budescu and Chen, 2015; Felin et al., 2017; Greenstein and Zhu, 2014; Jeppesen and Frederiksen, 2006; O'Mahony, 2003). In the funding of arts, crowds and experts vary in tastes: crowds are more likely to support projects that lack formality in proposals (i.e., using pictures and videos, informal language) (Mollick and Nanda, 2016). It remains unclear if crowd investors will exhibit such differences in tastes in the context of startup investing. On the one hand, crowd investors, unconstrained by decision-making norms and criteria in a field, may support more entrepreneurs who did not receive formal training to become an entrepreneur or who have unconventional career paths. On the other hand, since investing in startups via equity crowdfunding involves greater risks and information asymmetries, investment decisions are less likely to be based on individual preferences and tastes, but rather based on evidence of quality.

In sum, these explanations suggest that crowd investors may use similar evaluation criteria and heuristics as professional investors. Although the two groups may differ in tastes, if crowd investors and professional investors show high congruence in their preferences for startups and entrepreneurs they select, equity crowdfunding would not diversify investments. It would be a substitute, rather than complementary, source of capital.

4.4 Empirical Strategy

Understanding similarities and differences in funding decisions by crowds and professional investors requires startups of comparable characteristics (e.g., quality, founding team background, funding needs) to be evaluated by both types of investors. I therefore compared the funding outcomes of (i) startups that participated in equity crowdfunding ("ECF firms") and (ii) startups—of similar stages and business characteristics as ECF firms—that had the opportunity to participate but that did not crowdfund ("non-ECF firms" or "the risk set"). ECF firms were evaluated by crowd investors, while the non-ECF firms were evaluated by professional investors if they sought funding.

Comparing the funding outcomes of startups that participate in equity crowdfunding with startups in the risk set provides two key methodological benefits. First, it allows me to examine factors that drive resource allocation decisions for each of the two investor types. Specifically, I can compare how the funding outcomes of startups might vary depending on whether or not they crowdfund, and I can explore similarities and differences in firm and founding team characteristics of startups funded by each investor type.

Second, I can observe both the selection effect (i.e., factors that determine participation in equity crowdfunding) and the treatment effect among the selected individuals (i.e., differences in outcomes among startups that choose and do not choose equity crowdfunding as a funding source). Understanding the risk set is crucial in settings that involve self-selection into treatment, such as hiring or entry into entrepreneurship (Bennett and Chatterji, 2019; Fernandez and Weinberg, 1997; Sørensen and Sharkey, 2014). Since equity crowdfunding is a new form of mobilizing capital born from a regulatory change, researchers have both theoretical and policy interests in understanding the factors that determine participation in equity crowdfunding and whether it brings more benefits than traditional sources of capital. Taking into account these differences in the selected and risk set firms, I can then explore how differences in funding outcomes between the samples stem from selection and from participating in equity crowdfunding.

This selection effect provides more nuanced insights into my empirical question; however, this approach also adds challenges in isolating the treatment effect of equity crowdfunding because it would be difficult to randomly assign the intervention given that it is a regulatory change that occurred at the federal level. One way to estimate the treatment effect of the new regulatory change is to leverage cross-national data of treated and untreated regions, and then compare the pre-intervention outcomes with the post-intervention outcomes (Assenova, 2021; Eesley et al., 2016). While examining the treatment effect at the national level (i.e., the proportion of firms in a region that received funding) may offer a more precise estimate for how equity crowdfunding has changed the *rate* of funding, it does not inform whether equity crowdfunding has democratized capital access by shifting the *direction* of funding.

I prepared the sample for my analyses as follows. I first collected information on the universe of ECF firms that participated in Regulation Crowdfunding. Then, for each ECF firm, I identified the risk set of non-ECF firms—using firm age and industry to find startups of similar stage and business characteristics—at the time of an ECF firm's offering. Each firm decides to raise capital at different stages of its growth cycle, making it difficult to compare the funding outcomes of all startups during the same observation windows. Thus, for each ECF firm's offering, I measured funding outcomes since the equity crowdfunding deadline date ("ECF date"); for each non-ECF firm, I measured the outcomes using the same time window as the focal ECF firm. The analyses were conducted at the offering level. In other words, a firm that participated in two equity crowdfunding rounds in different years had two sets of risk set firms.

After constructing the sample, I first analyzed the selection process—namely, firm and founding team characteristics that affect the likelihood of participating in equity crowdfunding. In the second analysis, I examined the baseline effect of participating in equity crowdfunding—namely, whether equity crowdfunding, on average, improves funding outcomes of startups that participate (regardless of their firm and founding team characteristics). Understanding this baseline effect is important: if the average rate or amount of funding for ECF firms is not higher than non-ECF firms, equity crowdfunding may not be an efficient source of funding, calling into question whether it actually has the potential to democratize capital access. Further, the baseline effect serves as a proxy to unpack the relative importance of various firm and founding team characters among crowd and professional investors in their funding decisions, as explored in the main analyses. The main analyses address my research question by assessing whether equity crowdfunding changes the direction of funding and thus provides opportunities to underrepresented entrepreneurs typically overlooked by professional investors.

4.4.1 Regulation Crowdfunding Data

I collected data on all startups and small businesses participating in Regulation Crowdfunding from its inception in May 2016 through the end of March 2021 from two major sources: (i) offering statements available on the SEC's Electronic Data Gathering, Analysis and Retrieval (EDGAR) system and (ii) SEC-registered intermediary crowdfunding platforms. All firms that issue securities to non-accredited investors via Regulation Crowdfunding are legally required to file an offering statement, Form C, through the EDGAR system and with an intermediary crowdfunding platform of their choice. Form C requires firms to disclose information related to the business (e.g., websites, address, incorporated year, employee size), the offering (e.g., security type, minimum target amount, deadline date, maximum offering size, price per share, platform name, compensation to platforms), and financial statements for the last two fiscal years (e.g., revenue, net income, asset, debt). If a firm meets its target offering amount, it must file a progress update report, Form C-U, reflecting the total amount raised. Since funding amount information is not available for companies that do not meet their minimum goals, I supplemented the data with the funding outcome information on the publicly-accessible campaign pages of intermediary platforms. For offerings in which the campaign websites could not be found or were currently inactive,[10] I consulted two equity crowdfunding research platforms: KingsCrowd and CrowdLustro, which aggregate information on Regulation Crowdfunding offerings.

While there are a total of 3,568 equity crowdfunding offerings by 3,246 firms on 72 SEC-registered platforms, the sample used in the analysis covers 3,351 offerings by 3,040 unique startups on 25 platforms. From the original set of 72 platforms, 14 platforms are no longer operating, as they were merged into the other existing platforms (e.g., Nextseed, acquired by Republic), expelled by the SEC (e.g., uFundingPortal) or exited the equity crowdfunding market (e.g., StartWise). In addition, I excluded the 33 platforms that had fewer than 10 offerings. Most of the campaign pages on these inactive or small platforms are not publicly accessible, and thus excluded from the sample of ECF firms.

4.4.2 Constructing the Risk Set

Constructing the risk set requires a large database of startups with information about their characteristics and performance. To ensure that my analyses are based on representative and reliable samples of non-ECF firms, I used two large databases often employed in research on resource mobilization in entrepreneurship: Crunchbase and VentureXpert.[11] I constructed two different risk sets of non-ECF firms and compared the results across them. In the Results section, I present the findings using the risk set from Crunchbase as main results, because, compared to VentureXpert, Crunchbase

[10] Thirty-four percent of the campaign webpages (1,153 offerings) cannot be located.

[11] Crunchbase is a database of startup firms, financial organizations, affiliated individuals (e.g., executives and employees of startups, angel investors, VCs), investment and exit events. By crowdsourcing data from its large network of partnered organizations (e.g., accelerators) and its user community, Crunchbase covers a diverse range of companies and investors. The information is then manually verified for accuracy by its internal data team. While Crunchbase contains a broader spectrum of investor and company, VentureXpert, maintained by Thomson Reuters, focuses on VC firms and VC-backed companies. Despite the limited coverage of firms, VentureXpert has been widely used by researchers as it is considered to be one of the most accurate and comprehensive sources of information on VC investments and their portfolio companies (Kaplan and Lerner, 2017; Sorenson et al., 2016).

(i) contains more comprehensive information related to founding team backgrounds, including prior career history and education, and (ii) covers a greater number of ECF firms. The findings using the risk set from VentureXpert are available upon request and further discussed in Robustness Checks section.

Since the same set of firm and founding team information for ECF and non-ECF firms must be present for comparison, I limited the sample of ECF firms to those with company profiles on Crunchbase or VentureXpert. Among the sample of 3,040 ECF firms, 1,390 unique firms involved in 1,630 equity crowdfunding offerings were found on Crunchbase; 169 unique firms involved in 209 offerings were found on VentureXpert. To construct the risk sets, I identified all companies, excluding ECF firms, with the same industry categories and firm age as ECF firms at the ECF date. Assuming that each database covers the representative groups of startups in the U.S., the risk set consists of the population of all startups of similar stages and businesses "at risk" of participating in Regulation Crowdfunding.

To match industries, I used the industry categorizations on Crunchbase and VentureXpert. Crunchbase uses an industry group classification system which consists of 47 unique industry groups and is not mutually exclusive. In other words, a firm can be assigned to more than one industry group. I found exact matches for industry categorizations for 1,077 offerings. For the firms without exact matches, I conducted a nearest neighbor search using Hamming distance, which calculates the number of substitutions between two vectors. Specifically, I created a vector of industry dummies for each firm, and then calculated the pairwise Hamming distance between the two vectors. For the risk set from VentureXpert, I matched industries based on the industry classification system which consists of 69 unique industry groups. In VentureXpert, each firm is assigned to one industry group, and I composed the risk set of startups with the same industry group and firm age as the focal ECF firm. The risk set samples from Crunchbase and VentureXpert consist of 30,285 and 34,101 firm-year observations, respectively.

Although I aimed to construct a risk set of startups that share similar characteristics with the focal ECF firm, the two matching criteria—firm age and industry—cannot fully account for the underlying features of startups, such as startup quality and funding needs at the time of offering, which are difficult to observe and measure using archival data. Identifying the risk set with additional covariates, such as location and prior funding history, results in a smaller number of matched cases and can bias the results if the probability of matched cases is correlated with factors related to the relationship of interest (e.g., there will be fewer risk set cases for ECF firms in non-tech hubs). Nevertheless, in the Robustness Checks section, I discuss results using a risk set sample with more balanced firm characteristics.

4.4.3 Measures

Equity Crowdfunding Participation and Success

I used the variable *ECF* to distinguish ECF firms (value of "1") from non-ECF firms (value of "0"). The variable *ECF Success* takes a value of "1" for successful campaigns, which met the minimum target amount, and "0" for failed campaigns.

In the analyses based on the sample of ECF firms only (Table 4.9), I considered another measure of equity crowdfunding success: *ECF Amount* indicates the amount raised from crowd investors. I transformed the amount into logged values, as funding amount received from investors tends to exhibit highly skewed distribution (shown in Figure 4.1). If the amount raised could not be found in any of the mentioned sources, I coded the amount as zero. Conversations with the management team of one of the largest intermediary platforms confirmed that firms without this data are mostly firms with failed campaigns that requested to be removed from the platforms.

Funding Outcomes

Funding outcomes are measured from the ECF date until the end of March 2021 ("post-ECF period"). I compared the funding outcomes of ECF and non-ECF firms in two different ways: average funding rate and amount of funding. *Funding Received* takes a value of "1" if a firm has received at least one investment from either crowd or professional investors and "0" if it has not yet received any investment. The estimates using the binary variable can be interpreted as the average funding rate, or the likelihood of receiving any investment from investors. For ECF firms, *Funding Received* equals "1" only if they accomplished their minimum target amount because of the "all-or-nothing" scheme mentioned earlier. I calculated *Funding Amount* as the logged value of the total funding amount raised from any types of investors, among those who have received at least one investment (in other words, when *Funding Received* equals "1").[12]

For ECF firms, I distinguished funding received from each type of investors. To understand the funding outcomes of ECF firms without the presence of equity crowdfunding, I measured the outcomes excluding investments by crowd investors. The variable *Funding Received Excl. ECF* takes a value of "1" if a firm has received funding from professional investors only. For non-ECF firms, the variables *Funding Received* and *Funding Received Excl. ECF* have the same value, as none of the risk set firms participated in equity crowdfunding. Similar to the former variable, I measured *Funding Amount Excl. ECF* by calculating the logged value of total funding amount excluding the amount raised from crowd investors. To distinguish the amount received from crowd investors only, I measured *Funding Amount ECF Only* by using *ECF Amount* for ECF firms and *Funding Amount* for non-ECF firms.

[12]Fewer than 15 percent of startups in my sample received any investment from investors during the post-ECF period, so I excluded observations with zero values, as these could bias the estimates for funding amount.

Firm and Founding Team Characteristics

I also collected various firm and founding team characteristics, which are used as: (i) the factors that predict participation in equity crowdfunding, in the selection effect analysis; (ii) the control variables when examining baseline differences in funding outcomes between ECF and non-ECF samples; and (iii) the independent variables to assess how crowd and professional investors make funding decisions, in the main analyses.

I used two business attributes to construct the risk set sample: $Firm\ Age$ and $Industry$. To calculate firm age at the time of offering, I used the founding dates available in Form C documents for ECF firms, and Crunchbase and VentureXpert for non-ECF firms. I used the industry group classification systems available in the two entrepreneurship databases. For ease of interpretation, I grouped the 47 industry categories from Crunchbase into 14 broader industry groups. The list of these groups can be found in the descriptive statistics (Tables 4.1 and 4.2). As firms can be assigned to multiple groups on Crunchbase, I introduced a control for $Industry\ Counts$, which captures the number of unique industry categories assigned to a firm.

Professional investors typically prefer to invest in startups engaging in high-technology industries. To understand whether equity crowdfunding helps entrepreneurs in underrepresented industries (i.e., non-high-technology industries), I coded $HighTech$ as "1" if a firm engages in one of the following industry groups—$AdvancedScience$, $AppPlatform$, $BiotechHealth$, $InfoTech$, $Hardware$, and $Software$—and "0" otherwise. Based on Crunchbase data, investments in $HighTech$ firms account for 71 percent of deal counts and 66 percent of deal volumes in the U.S. between 2016 and 2020.[13]

Whether a firm has previously raised capital has been a common indication of

[13] I included all investments into the U.S.-based firms, excluding equity- and reward-based crowdfunding, initial coin offering, and grant deals.

future success for professional investors (Bapna, 2019; Shane and Stuart, 2002). To assess whether crowd investors and professional investors look for similar evidence of quality, I included *Previously Received Funding*, which takes a value of "1" if the company has received any amount of funding from professional investors before the ECF date, and "0" otherwise.

Firm location is a strong determinant factor for VC funding (Dahl and Sorenson, 2012; Guzman and Stern, 2015; Stuart and Sorenson, 2003), as such I explore whether entrepreneurs located in regions without VC presence benefit from equity crowdfunding. The variable *VC Region* is measured as the logged value of the average number of VC investments (classified as "seed" or "early" stage on VentureXpert) in the county where the firm is located. Instead of measuring the number of VC investments during one year, I took the average over the three-year window prior to the ECF date. This approach accounts for potential noise from year-to-year fluctuations.

I created various measures that capture the human capital and social capital of founding teams, which professional investors emphasize when making funding decisions (Beckman et al., 2007; Gompers et al., 2020; Hsu, 2007; Roche et al., 2020; Shane and Stuart, 2002). I considered individuals as founding members if they are listed as "executives" on Crunchbase. I excluded individuals listed as "employees" or "board members," as it is unclear how much of an active role they have played in managing the operations and resource mobilization processes. Since my sample consists mostly of small, early-stage startups, with an average firm age of 5.7, it is reasonable to believe that individuals who have held executive positions are the key founding members. *Team Size* measures the number of founding members listed in the database.

Founder Experience captures whether any of the founding members have previously had a role as a founder prior to the establishment of the focal startup.[14] I

[14] I used the keywords "entrepreneur," "founder," "founding partner," "founding ceo," and "owner" to classify whether a founding member has previously had founder experience.

also included two measures for educational affiliation of founding members to understand how it affects resource allocation decisions of crowd investors and professional investors. *VC Schools* takes a value of "1" if any of the founding members received a degree from one of the top 10 universities that produce the most venture capitalists, and "0" otherwise.[15] It is unclear whether the observed differences in the effect of attending *VC Schools* among the crowd and professional investors are driven by signals related to human capital (e.g., quality or capability of founders) or social capital (e.g., shared affiliation with professional investors). The top 10 schools that produce the majority of VC professionals tend to be highly-ranked, prestigious institutions, whose alumni could be perceived as having superior human capital. To disentangle the mechanisms related to social capital from those related to human capital, I included *University Prominence*, which measures the maximum prestige of founding members' alma maters. I followed the approach of Rider (2012) and Hallen et al. (2020) to capture the university prominence of founding teams by applying *U.S. News & World Report's* global university scores.[16] In 2021, *U.S. News and World Report*'s assigned scores ranging from 24 to 100. Founders who either did not attend university or whose educational background information could not be located on Crunchbase were assigned a ranking of 23, one below the lowest listed score.

To understand whether equity crowdfunding aids capital access to gender and racial minority entrepreneurs, I examined how the demographic composition of founding teams differently affects investment decisions by crowd and professional investors. To identify founding member gender, I used a matching algorithm from the R package "gender" (Blevins and Mullen, 2015). The package uses an individual's first name

[15]The list includes Harvard University, Stanford University; University of Pennsylvania; Massachusetts Institute of Technology; Columbia University; Yale University; Dartmouth College; University of California, Berkeley; University of Chicago; Cornell University; Princeton University; and University of Michigan, Ann Arbor. The top 10 list from Crunchbase roughly resembles the top VC school list in Rider (2012)'s study, which relied on the Greyhouse Directory of Venture Capital and Private Equity Firms.

[16]https://www.usnews.com/education/best-global-universities/rankings

as an input and matches it with historical data of varying time periods and regions to calculate the proportion of male and female uses of a name. Specifically, I used the record of names in the Social Security Administration (SSA) since 1950 as the source to generate the proportions. I identified a founding member as “female” if the proportion of female individuals with a given name was greater than 60 percent, and “male” if the proportion of male individuals with a given name was greater than 60 percent. I recorded the remaining names with a lower probability of a given gender (i.e., gender neutral names) as missing. To identify race/ethnicity group for each founding member, I used an algorithm from the R package “wru” (Imai and Khanna, 2016). Similar to the gender matching algorithm, it combines the Census Bureau’s Surname List with geocoded voter registration records to generate the probability of each race/ethnicity group category—“Asian or Pacific Islander,” “Black,” “Hispanic or Latino,” “White,” and “Other or Mixed”—for a given surname. From there, I identified the racial/ethnic category of a founding member by choosing the category with the greatest probability for a given surname. I recorded individuals with surnames not included in the historical databases or those classified as “Other or Mixed” as missing. To construct a firm-level measure of demographic composition, I used the proportion of certain gender and race/ethnicity groups in a founding team. Specifically, I calculated *Prop. Female* using the proportion of female individuals among individuals with identified gender information. I used the variables *Prop. Asian*, *Prop. Black*, and *Prop. Hispanic* to indicate the proportion of founding members in each non-white group. The variable $MissingDemoInfo$ is set to “1” if demographic background information for teams is missing or if founding member information could not be found in the database.

Table 4.1 provides descriptive statistics for the firms that have participated in Regulation Crowdfunding. Table 4.2 meanwhile presents descriptive statistics of the paired ECF firms and the risk set of non-ECF firms used in the main statistical analyses.

[Table 4.1]

[Table 4.2]

It is likely that firms with company profiles on Crunchbase, relative to those without profiles, differ by various firm characteristics. Most notably, the firms from Crunchbase used in the analyses are more likely to be high-growth startups engaged in new technologies or entering new markets (e.g., solar technology, biotechnology), as opposed to low-growth small businesses engaged in traditional existing markets (e.g., local distillery, gym) (Botelho et al., 2021). Descriptive information shows that ECF firms used in the analyses, relative to the universe of startups that participated in Regulation Crowdfunding, received more funding from crowd investors (3.67 in Table 4.1 and 4.99 in Table 4.2). ECF firms in the analyses are also more likely to engage in high-technology industries (0.38 in Table 4.1 and 0.60 in Table 4.2). Thus, I assessed whether startups with certain businesses and founding team characteristics are more or less likely to be profiled on Crunchbase. Table 4.3 shows that firms with proven track records, in terms of crowdfunding success, valuation amount, employee size, and located in regions with more professional investors are more likely to be included in the ECF sample used in the analyses. In the Results section, I discuss how the representation of ECF firms in the analysis sample affects the interpretation of key findings.

[Table 4.3]

4.5 Results

4.5.1 Selection Effect: Decisions to Mobilize Resources from Crowd Investors

I first examined the factors that determine the likelihood of choosing equity crowdfunding as a funding source, as shown in Table 4.4. While the models cannot account for unobserved factors (i.e., funding needs, personality or vision of entrepreneurs),[17] the results nonetheless highlight several key firm and founding team characteristics that may affect an entrepreneur's decision to participate in equity crowdfunding.

I find firms that previously received funding are, on average, 4 percent more likely to participate in equity crowdfunding (Model 1). Underrepresented entrepreneurs, both in terms of shared educational and professional experience with (i.e., lack *Founder Experience* and do not hold a degree from *VC Schools*) and locations near more professional investors (i.e., located in non-*VC Region*), do not have a greater likelihood of participating in equity crowdfunding relative to entrepreneurs more socially and spatially proximate to professional investors. Yet the coefficient of *VC Region* in Table 4.3 shows that ECF firms included in the analyses are more likely to be located in regions with greater VC presence, relative to ECF firms not included in the analyses; therefore, I may be underestimating the effect of *VC Region* in Table 4.4.

However, I find evidence that founding teams with more gender and racial minorities are more likely to choose equity crowdfunding as a funding source. For instance, all-female or all-Black founding teams have 2 percent and 8 percent greater likeli-

[17]The omitted unobserved factors may explain why the R-squared values are relatively small compared to other models in this paper. For example, whether a non-ECF startup was looking for funding opportunities at the ECF date is an important selection factor, yet it is impossible to collect such information for the risk set of startups. While I considered prior funding history as a proxy for the quality of startups, the analysis may not fully capture unobservable qualities such as entrepreneurs' personality or vision.

hoods of participating in equity crowdfunding, compared to founding teams without any female or Black members. It is promising to see interest from entrepreneurs from minority groups historically facing disproportionate challenges raising capital from professional investors (Deloitte and Venture Forward, 2021; Thébaud, 2015), but further investigation into whether these entrepreneurs have better funding outcomes is needed to assess if equity crowdfunding can democratize capital access.

[Table 4.4]

4.5.2 Baseline Effect: Equity Crowdfunding and Funding Outcomes

Next, I examined the average difference in funding outcomes between startups that mobilized resources from the crowd and those that did not crowdfund, as illustrated in Table 4.5. Firms participating in equity crowdfunding have, on average, a 67 percent greater likelihood of receiving investment (Model 1). The increased funding rate is mostly driven by firms that achieve *ECF Success*, while those that participated but failed to meet their targets have a similar funding rate as non-ECF firms (Model 2). Among firms that receive at least one investment, firms funded by the crowd receive, on average, 90 percent ($(e^{-2.27} - 1) \times 100$) less funding than firms backed by only professional investors (Model 3). This lower amount can be explained by the Regulation Crowdfunding investment size limit of \$1.07 million (until March 2021), compared to no limits on the size of investments for professional investors. ECF firms that achieved crowdfunding success received smaller funding amounts than non-ECF firms. The failed ECF firms, if they had secured funding from professional investors, received a greater average funding amount than successful firms, though the amount is less than that of non-ECF firms (Model 4). Excluding the amount raised from crowd investors, the average funding rate of ECF firms does not meaningfully differ from that of non-ECF firms (Models 5 and 6).[18]

In sum, allowing startups to mobilize resources from crowds provides greater access to capital by increasing the average funding rate for participating firms, relative to those that do not crowdfund, even if the amount is lower due to regulatory caps. The next analysis investigates whether it has also changed the direction of funding by diversifying investments and supporting underrepresented entrepreneurs.

[Table 4.5]

4.5.3 Does Equity Crowdfunding Democratize Capital Access?

To elucidate further what types of startups and entrepreneurs realize the benefits from equity crowdfunding, and whether they are from underrepresented groups, I examined firm and founding team characteristics funded by crowd and professional investors. Tables 4.6 and 4.7 explore the relative importance of these characteristics—specifically, evidence of quality, educational and professional background of founding teams, demographic composition of founding teams, and firm location—on funding outcomes, measured as *Funding Received* and *Funding Amount ECF Only*, respectively. The first two models in the table apply subgroup analysis to understand the factors that predict resource allocations for crowd investors and professional investors, separately. The third and fourth models include all ECF and non-ECF firms, and I used firm and team characteristics as moderators. The coefficient for each characteristic represents the interaction effect of ECF and that characteristic. The interaction terms in these models indicate the relative importance of an attribute among crowd investors (who invest in ECF firms) and professional investors (who

[18]These models do not capture the opportunity costs (e.g., ECF firms would have chosen alternative sources of financing) and cannot fully rule out the selection concerns related to unobserved characteristics (e.g., non-ECF firms may not have funding needs). However, the differences in the ECF coefficient in Models 1 and 5 are worth considering.

invest in non-ECF firms). I discuss the findings by firm and founding team attribute. In the Summary of Main Results section, I summarize the key implications of these findings.

[Table 4.6]

[Table 4.7]

Evidence of Quality. Both crowd and professional investors consider prior funding history to be an important factor when reviewing investment opportunities. Table 4.6 shows that having prior funding history increases the funding rate by 12 percent for ECF firms (Model 1), but by only 3 percent for non-ECF firms (Model 2). The positive and significant interaction terms in Model 3 also provide evidence that crowd investors, relative to professional investors, pay more attention to this evidence of quality. Yet conditional on receiving an investment, receiving prior funding plays a much larger role in the average amount received from professional investors than from crowd investors (Table 4.7). These results suggest that crowd investors attend to signals of quality similar to professional investors, consistent with prior research on the wisdom of crowds (Mollick and Nanda, 2016).

Human Capital of Founding Teams. Next, I examine whether the human capital of founding teams—namely, founder experience and educational affiliation—which are strong determinants of social ties with and funding by professional investors may still be important deciding factors for crowd investors. The relative importance of $Founder\ Experience$ on the funding rate is not significantly different between ECF and non-ECF firms (Table 4.6). However, it strongly predicts average funding amount for non-ECF firms but less so for ECF firms (41 percent vs. 5 percent; Models 1 and 2 in Table 4.7). Graduating from $VC\ Schools$ increases the average funding rate for non-ECF firms by 6 percent and the average funding amount by 48 percent (Model 2 in Tables 4.6 and 4.7); however, this factor is not significant in determining funding decisions by crowd investors (Model 1 in Tables 4.6 and 4.7). The difference in the relative importance of educational background between the two investor groups is statistically significant (Model 3 in Tables 4.6 and 4.7).

Taken together, past career and educational experience are not significant predictors of crowds' funding decisions, though these factors are strongly associated with professional investors' funding decisions. These results alone do not explain the mechanism that drives this difference. Drawing from previous research, possible explanations include: (i) crowd investors care less about the *human capital* of entrepreneurs (i.e., educational attainment), and (ii) *social capital* of entrepreneurs (i.e., shared affiliation with VCs) plays a much smaller role among crowd investors. To distinguish the "social capital effect" from the "human capital effect," I replaced the educational affiliation variable, $VC\ Schools$, with $University\ Prominence$, in Model 4, as detailed in Tables 4.6 and 4.7. The variable $VC\ Schools$ captures both effects (i.e., educational attainment *and* shared affiliation with VCs), as the top 10 VC schools tend to be highly ranked, prestigious schools as well; however, $University\ Prominence$, which measures the school ranking of universities, should have a positive relationship with only human capital (i.e., educational attainment) of entrepreneurs. For example, Johns Hopkins University is a prominent school, ranked number 10 in the *2021 U.S. News Best Global Universities*, but it is not one of the top 10 schools for professional investors.

If we find consistent effects of educational affiliation using the two variables, this could imply that crowd investors are paying less attention to the signals related to founding teams' human capital. Yet if we find no meaningful difference in the relative importance of $University\ Prominence$, this could imply that crowd and professional investors similarly pay attention to human capital signals, but that investment decisions by crowd investors are less likely to be driven by mechanisms related to social capital (i.e., shared professional experience or educational affiliations with professional investors). Results using $University\ Prominence$ reveal that the effect of

VC Schools is driven by mechanisms related to social capital. The coefficients related to the relative importance of *University Prominence* are close to zero in both tables. This evidence suggests that equity crowdfunding has helped entrepreneurs, who have been underrepresented due to a lack of shared professional experience and educational affiliation with professional investors, gain access to capital.

Demographic Composition of Founding Teams. It is important to understand whether the introduction of crowd investors has reduced gender and racial disparities in startup funding. Table 4.6 shows that there is no meaningful difference in the proportion of female founding members between ECF firms funded by the crowd and non-ECF firms funded by professional investors (Model 3). I likewise do not find significant differences in the average funding rates based on the proportion of Asian or Pacific Islander team members for both types of investors. Further, founding teams with more individuals from Black and Hispanic backgrounds are less likely to receive investment, regardless of investor type (Model 1 and 2), and the extent of racial bias between the two groups does not significantly differ.

Conditional on receiving an investment, however, firms with a higher percentage of Black and Hispanic founding members receive a greater amount of funding when they mobilize financial resources from crowd investors (Table 4.7). While the differences in the coefficients related to *Prop. Black* and *Prop. Hispanic* in the ECF and non-ECF samples are not statistically significant, firms with all-Black founding members, on average, receive 63 percent more funding if they receive investments from crowd investors instead of professional investors; firms with all-Hispanic founding teams, on average, receive 1.6 times greater funding when they choose equity crowdfunding as the funding source (Model 3). Based on this evidence, crowd investors appear to have higher standards for evaluating investment opportunities for firms founded with more Black and Hispanic team members. Yet once these firms start to gain traction, they may be able to receive more capital. I find the opposite pattern for *Prop. Female* and *Prop. Asian*. Specifically, founding teams with all-female or all-Asian founding members tend to receive 35 percent and 44 percent less funding, respectively, from crowd investors relative to professional investors.

Overall, I do not find strong evidence supporting a reduction in gender and racial biases among crowd investors. Firms with more Black and Hispanic members have a lower average likelihood of receiving investment from equity crowdfunding; female-led or Asian-led firms likewise do not find substantial improvement in capital access. Among firms that secured funding, those with more female and Asian team members receive lower amounts on average.

Geographic Location. To understand whether equity crowdfunding diversifies the geographic distributions of investments, I examined the relative importance of VC presence in a county where a firm is located. When the funding outcome is measured in terms of funding rate, I do not find a statistically significant difference in the relative importance of VC presence in a region between the two types of investors (Model 3 in Table 4.6). Yet, as shown in Table 4.4, many firms located in regions with less VC capital are excluded from the sample used in my analyses.[19] Thus, I may be underestimating the effect of geographic location if I'm pooling a sample of ECF firms from regions where many professional investors are located (and non-ECF firms that are engaging in industries that attract more VCs).

Table 4.7, however, shows that a percent increase in the level of VC investments in the firm's county is associated with a 22 percent higher funding amount (Model 2), while being located in a $VCRegion$ does not affect the funding amount received by ECF firms (Model 1). The negative and significant interaction coefficient in Model 3 implies a reduced location bias when the locus of startup investment decisions moves from the small circle of professional investors to the broader population of crowd

[19]The mean value of $VCRegion$ in the full sample of startups that participate in equity crowdfunding is 3.6 (Table 4.1), while the mean values of ECF firms and non-ECF firms "at risk" used in the analyses are both approximately 4.0 (Table 4.2).

investors.

As mentioned above, the sample used in the statistical analyses does not fully represent the geographic distributions of firms participating in equity crowdfunding. To address whether equity crowdfunding aids capital access for entrepreneurs from previously secluded regions, I examined the geographic distributions of startups funded by the crowd and those funded by VCs. Figure 4.3 illustrates the county-level ratio of (i) the total amount of investments by crowd investors in all successful Regulation Crowdfunding offerings to (ii) the total amount of investments by venture capitalists in "seed" or "early-stage" deals between 2016 and 2020. In other words, I calculated the proportion of amount raised from equity crowdfunding (or from VCs) in a county, and then compared the proportions of the two resource provider types in a county. If equity crowdfunding provides funding to entrepreneurs located in regions with greater VC presence—and that crowd investors are competing with professional investors for firms in selected locations—then we would expect all counties to be in yellow shaded areas, which indicate that there is a similar concentration of investments from VCs and the crowd. Rather, most counties are either dark red, indicating that VCs dominate the startup financing landscape (e.g., Santa Clara County, California), or dark blue, indicating that crowds are the sole source of funding (e.g., San Bernardino, California). The visual representation based on all equity crowdfunded and VC-backed offerings provides further evidence that equity crowdfunding has improved capital access for startups spatially distant from professional investors.

[Figure 4.3]

Industry. To investigate whether crowd and professional investors differ in industry preferences when making startup investment decisions, I compared the funding outcomes among firms in high-technology industries and non-high-technology industries. Since I employ industry fixed effects across all models, I conducted subgroup analyses to observe industry differences in Table 4.8. Specifically, using the same specifications in Model 1 in Table 4.5 and Model 3 in Table 4.6, I show the estimates among firms engaging in high-technology (Models 1 and 2) and non-high-technology industries (Models 3 and 4).

Firms are more likely to benefit from participating in equity crowdfunding if they engage in non-high-technology sectors. The likelihood of receiving funding increases by 71 percent if a non-high-technology firm participates in equity crowdfunding (Model 3), whereas the average funding rate increases by 65 percent for a high-technology firm (Model 1). Equity crowdfunding has provided additional capital access to firms not in high-technology industries, suggesting that these firms that are less preferred by professional investors that seek to invest in high-technology firms with innovative, proprietary technology.

Table 4.8 also illustrates how the biases and preferences of crowd investors and professional investors vary across industries (Models 2 and 4). Most notably, the relative importance of having a degree from $VC\ Schools$ among crowd investors is significantly lower for high-technology firms, which have historically attracted more professional investors; however, the role of educational background does not significantly differ between the two investor types for non-high-technology firms. Less technology-driven firms with more Black and Hispanic entrepreneurs have a significantly lower chance of receiving investments if they decide to mobilize resources from the crowd, yet the racial bias by crowd investors is not magnified in high-technology industries. One possible explanation is that the crowd is more likely to hold a stereotypical assumption about the quality of racial minority entrepreneurs (i.e., less capable of operating a business) if they engage in non-high-technology businesses (e.g., local distillery, gym) rather than high-technology businesses, which often require higher education and scientific expertise.

[Table 4.8]

4.5.4 Summary of Main Results

To summarize, I find that crowd and professional investors share similarities and differences in their resource allocation decisions. Consistent with prior research on other pre-existing forms of crowdfunding (Agrawal et al., 2014; Mollick and Nanda, 2016), the evaluation by crowds is driven by rational decision-making based on the evidence of quality. Specifically, I find that crowd investors, even more so than professional investors, look for evidence of quality, namely whether a firm has previously raised capital from other investors.

Second, I find that some types of underrepresented entrepreneurs realize the benefits from the new source of capital. In contrast to professional investors who prefer startups founded by individuals with prior founder experience and those who come from the same educational institutions (Beckman et al., 2007; Gompers et al., 2020; Hsu, 2007; Shane and Stuart, 2002), the professional and educational backgrounds do not strongly predict crowd investors' funding decisions. While crowd and professional investors do not differ in terms of how they value human capital (i.e., university prominence) of founding teams, the investments by crowd investors, unlike professional investors, are less likely to be driven by the social capital of founding teams. I also observe that startups located in regions with lower rates of VC physical presence and startups engaging in non-high-technology industries can experience greater advantages from equity crowdfunding. Taken together, having shared professional and educational affiliation with, being closely located with, and engaging in industries preferred by professional investors do not appear as valuable when receiving investments from the crowd. Social and spatial proximity, which largely explain resource exchange dynamics in many economic contexts, including entrepreneurship (Canales and Greenberg, 2016; Guzman and Stern, 2015; Hegde and Tumlinson, 2014; Hochberg et al., 2007; Sorenson and Stuart, 2001), may not apply to settings that involve crowds as resource providers.

However, results regarding gender and race/ethnicity composition of founding teams call into question the ability of crowd investors to democratize capital access. While we observe greater participation among startups with more female and racial minority entrepreneurs, these startups do not have better funding outcomes from looking to the crowd, relative to professional investors. Firms with greater proportions of Black and Hispanic founding members have a lower average funding rate, but, conditional on receiving investment, these same firms receive a greater average funding amount from crowd investors. This suggests that there could be higher appraisal standards when crowd investors decide to invest in firms with founders from these racial/ethnicity groups. Firms with more female and Asian team members have, on average, higher funding rates but tend to receive lower funding amounts from crowd investors. Results on racial bias is somewhat consistent with findings from prior research on lower-stakes, reward-based crowdfunding context. Younkin and Kuppuswamy (2018) shows that Black entrepreneurs are less preferred over White entrepreneurs, despite accounting for taste-based (i.e., perceived quality) and statistics-based discrimination (i.e., founder quality, likelihood of support). Widespread unconscious bias—for this study the assumption that Black and Hispanic entrepreneurs are of lower quality—appears to persist and is not corrected by diversifying the pool of resource providers. In particular, the racial bias prevails among firms engaging in non-high-technology sectors, which require less expertise and education than firms engaging in high-technology sector. Contrary to evidence that crowd investors are not "color-blind," a field experiment study shows that crowd investors, especially the ones with fewer experiences and less expertise, are more likely to be "gender-blind" (Bapna and Ganco, 2021). Yet I find that female entrepreneurs are still penalized, even if they pursue equity crowdfunding. Perhaps we are not observing enough diversity from the resource supply-side—namely, female and racial minority crowd investors—who are willing to support entrepreneurs with shared social identities (Greenberg and Mollick, 2017; Kleinbaum et al., 2013).

4.5.5 Post Hoc Analysis: How Does Equity Crowdfunding Affect Future Performance?

To assess whether equity crowdfunding is a sustainable funding source for entrepreneurs, I investigated the longer-term consequences of participating in the new source of entrepreneurial capital. Specifically, I examined how equity crowdfunding success or failure affects future performance and survival. As in the main analyses, it would be ideal to compare these outcomes with non-ECF firms "at risk" of participating in ECF. However, while this detailed firm outcome information (e.g., revenue, employee size) is publicly disclosed for firms that participate in Regulation Crowdfunding, gathering such information for non-ECF firms is difficult, as they are not legally required to disclose this information. Nonetheless, comparing ECF firms that have successfully raised capital from crowd investors, relative to ECF firms that failed to raise capital, informs whether equity crowdfunding could allow startups to grow their businesses, receive subsequent funding from professional investors and create more jobs in the long run.

Table 4.9 shows how successful crowdfunding offerings (*ECF Success*; Panel A) and amount raised from crowd investors (*ECF Amount*; Panel B) affect firm failure (*Failure*), the likelihood of receiving funding from professional investors (*Future Funding Received*), as well as, number of employees (*Employees*), revenue (*Revenue*) and net income (*Net Income*) in the following year.[20] I limit the

[20] I collected data on firm failure by checking whether the company website is accessible and by tracking social media profiles of each firm. I recorded *Failure* as "1" if the company website cannot be located and if there has not been any social media posts over the past six months (at the time of data collection on early May 2021), and "0" otherwise. Among all firms that participated in Regulation Crowdfunding, 9 percent failed. I collected post-ECF date funding information from Crunchbase. The binary variable *Future Funding Received* takes a value of "1" if the company has received funding from professional investors after the ECF date. I collected employee, revenue and net income information from Form C-AR documents, annual reports that must be submitted to the SEC if a firm has successfully raised capital from crowd investors at least once.

analysis to 3,200 offerings (by 2,900 unique firms) until the end of 2020 in order to allow sufficient observation windows in which to observe post-equity crowdfunding outcomes.

The models in Table 4.9 indicate that crowd investments appear to be associated with a 9 percent decrease in firm failure rate (Model 1 in Panel A) and a one percent increase in the amount raised from crowd investors is associated with a 2 percent lower firm failure rate (Model 1 in Panel B). Given the evidence that the majority of startups fail (Startup Genome, 2019; U.S. Bureau of Labor Statistics, 2016), this finding suggests that successfully mobilizing resources from crowd investors is associated with a significantly improved survival rate for early-stage firms (or alternatively, that crowd investors can successfully predict winning firms). Running a successful equity crowdfunding campaign may also serve as a positive quality signal for professional investors. Startups that had a successful campaign and raised more funding are more likely to attract professional investors in the future, relative to those that had a failed campaign and received less funding (Model 2 in Panels A and B). Achieving *ECF Success* is not significantly associated with employee size and financial performance in the following year (Models 3 to 5 in Panel A). However, a one percent increase in crowd investment amount is associated with 5 percent and 7 percent increases in employee size and net income, respectively (Models 4 and 5 in Panel B). As such, the new form of mobilizing resources from the crowd is positively associated with firm survival, subsequent funding from professional investors, job creations and profitability for startups and small businesses. Equity crowdfunding thus has the potential to improve not only short-term funding outcomes but also longer-term performance and survival for early-stage startups.

[Table 4.9]

4.5.6 Robustness Checks

Despite my efforts to account for any other firm heterogeneity by including various firm and founding team characteristics in my models, there are several difficult-to-observe factors that could affect both selection into equity crowdfunding and funding outcomes, such as the quality of startups and founding teams, the funding needs of non-ECF firms and whether ECF firms have attempted to raise capital from professional investors. To address whether this selection concern affected my results, I ran several robustness checks. Specifically, I conducted the main analyses with samples of ECF and non-ECF firms with more balanced characteristics, reconstructing the risk set in two ways: (1) adding *Previously Received Funding* as an additional covariate (1,438 ECF-firms and 18,037 non-ECF firms), and (2) using nearest neighborhood matches based on *Previously Received Funding Amount* and *VC Region* to compare each ECF firm with the non-ECF firm most similar in terms of firm age, industry, prior funding history and firm location (1,622 pairs of ECF and non-ECF firms).

Overall, the patterns (tables available upon request) are consistent with the main results. In both samples, participating in equity crowdfunding is associated with greater funding rate, although the average funding amount provided by the crowd is lower than the average amount provided by professional investors, in line with Table 4.5 results. In addition, the relative effects of firm and founding team characteristics remain robust, although the level of significance for demographic characteristics and VC Region when I use the nearest neighborhood matching strategy, most likely due to the smaller sample size. Results show that crowd investors, compared to professional investors, are more likely to fund startups with prior funding histories and located in counties with fewer VCs. The relative importance of founder experience, shared educational affiliation and location is much smaller among crowd investors. I consistently find that firms with more Black and Hispanic founding members have no advantage in terms of the likelihood of receiving an investment, although the average amount received by firms with more Black entrepreneurs is higher if investment is secured. These analyses also show consistent gender bias among crowd investors.

4.6 Discussion

This paper investigates whether allowing crowds to invest in startups democratizes capital access by examining similarities and differences in firm and founding team characteristics of startups funded by crowd investors compared to professional investors. To answer this question, I collected novel data on the universe of firms that had participated in Regulation Crowdfunding, and compared funding outcomes of these firms with the risk set of firms—of comparable stages and businesses—that did not crowdfund. I find mixed results related to whether equity crowdfunding democratizes capital access. Equity crowdfunding provides benefits to some groups of entrepreneurs, but not all. Whereas professional investors prefer entrepreneurs who have prior founder experience and are likely to have attended the same universities, such professional and educational experiences do not influence crowd investors' funding decisions. Moreover, equity crowdfunding provides more benefits to startups located where professional investors are not present and those that do not engage in high-technology industries, which have historically attracted more professional investors. However, crowd and professional investors are similarly biased towards female and racial minority entrepreneurs. Although firms with greater proportions of female, Black and Hispanic founding members are more likely to pursue equity crowdfunding, crowd investors are less likely to invest in these startups. The long-term implications of gender and racial/ethnic gaps in startup financing is concerning, as crowd investment is strongly associated with the survival, subsequent financing, job creation and profitability of startups.

These findings contribute to our knowledge about resource mobilization in entrepreneurship (Canales and Greenberg, 2016; Hegde and Tumlinson, 2014; Hochberg et al., 2007; Rider, 2012; Sorenson and Stuart, 2001; Stuart and Ding, 2006; Stuart and Sorenson, 2007). Specifically, results show that the resource exchange dynamics in entrepreneurship, deeply rooted in shared affiliations and pre-existing relationships with professional investors, have evolved with the introduction of equity crowdfunding. Social and spatial proximity to professional investors, which strongly influence a startup's funding outcome, is less consequential when receiving investment from crowd investors. This research offers evidence that equity crowdfunding plays a role in overcoming structural barriers for entrepreneurs who are underrepresented in terms of professional and educational background, location and industry. An important scope condition for these social mechanisms is that there needs to be a diverse group of individuals participating in equity crowdfunding as investors. The persistent disadvantages towards female and racial minority entrepreneurs could be explained by not having enough representation of these social groups among crowd investors.

This study also contributes to the growing body of work on the role of crowds in organizational outcomes (Agrawal et al., 2014; Cumming et al., 2021; Mollick, 2014; Mollick and Nanda, 2016; Piezunka et al., 2021; Piezunka and Dahlander, 2015; Sorenson et al., 2016; Yu et al., 2017). Over the past decade, technological advances have led to the emergence and popularity of online platforms, increasing the role of crowds in affecting organizational outcomes, a shift from the historically small number of expert professionals with influence in this space (Botelho, 2018; Piezunka and Dahlander, 2015). Scholars have started to examine how crowds and experts vary in resource allocation decisions, especially in the context of reward-based crowdfunding (Agrawal et al., 2014; Greenberg and Mollick, 2017; Mollick and Nanda, 2016; Sorenson et al., 2016; Younkin and Kuppuswamy, 2018). I build on this line of inquiry by examining how crowd and experts vary when making decisions in the context of startup evaluation, as characterized by high levels of information asymmetry, risks and uncertainties (Anton and Yao, 1995; Botelho and Chang, 2022; Hegde and Tumlinson, 2014; Scott et al., 2020). My findings on the persistence of gender and racial biases provide evidence that crowd investors, who make resource allocation decisions under uncertainty, perpetuate, rather than correct, biased evaluations (Botelho, 2017; Salganik et al., 2006). Crowd investors can have far-reaching impact on organizational outcomes, as they become shareholders of startups. We have yet to learn how this shift in the number and composition of investors impact later organizational processes and outcomes, such as managing and hiring practices.

This study would also be of interest to scholars examining the role of human capital in affecting the evolution of entrepreneurial organizations (Baron et al., 2001; Beckman and Burton, 2008; Beckman et al., 2007; Hsu, 2007; Kacperczyk, 2013; Stuart and Ding, 2006). The results from comparing two measures of educational attainment—namely, (i) whether a founding member has attended the top 10 schools that produce professional investors and (ii) the maximum prominence of schools that founding members have attended—spark an interesting discussion related to different mechanisms through which the human capital of founding teams affects entrepreneurial outcomes. The proxy for human capital appears to be valuable because it is closely tied with the social capital of entrepreneurs, rather than because it conveys a signal related to the quality of founding teams.

Motivated by the new regulation on entrepreneurial finance, this study provides evidence that institutional changes and reforms have a profound effect on the survival and growth of entrepreneurial organizations (Assenova, 2021; Canales, 2016; Eesley et al., 2016). Evidence for the effectiveness of equity crowdfunding on removing some barriers to capital access can add to the growing body of work on how institutional changes can serve as critical enablers of entrepreneurship. While I focus on how equity crowdfunding has, to some degree, democratized capital access by examining differences in startups funded by crowd investors and professional investors, future research can examine the effectiveness of equity crowdfunding at the economy level by estimating the treatment effect by comparing countries with and without similar regulatory reforms.

Finally, this paper contributes to scholarly and policy discussion on various forms of inequality in entrepreneurship, including gender and racial disparities (Bapna and Ganco, 2021; Thébaud, 2015; Thébaud and Sharkey, 2015; Younkin and Kuppuswamy, 2018). That crowd investors, compared to professional investors, are equally or more biased towards female and racial minority entrepreneurs suggests that removing structural barriers to capital access may not be enough. One potential explanation for the persistent gender and racial inequalities in entrepreneurship is that crowd investors, who are faced with more information asymmetries and have fewer experiences in evaluating startups, are more reliant on heuristics, such as the stereotypical assumption about the quality of these entrepreneurs. This calls for more active interventions involving investors and intermediaries to provide more access to these underrepresented entrepreneurs. Another plausible explanation is that equity crowdfunding has not yet diversified the pool of resource providers. It is unclear whether the background and composition of crowd investors are similar or substantially different from professional investors. Exploring how the characteristics of the crowd (e.g., expertise, socioeconomic status) affect startup investment decisions suggests a path for future research.

Understanding whether equity crowdfunding democratizes capital access is important from a policy perspective. While some policymakers and practitioners consider equity crowdfunding to be a "game changer" in the startup financing landscape, others have viewed it with cynicism, casting doubt on whether it could serve as a legitimate funding source and complement traditional sources of capital (Andersen, 2013; Mims, 2015; Stanford, 2020). This study is timely given that the SEC recently increased the maximum offering amount for a 12-month period by fivefold, from $1.07 million to $5 million, thereby encouraging more entrepreneurs and investors to participate in equity crowdfunding. My findings suggest that equity crowdfunding success has the potential to create a positive impact on firm survival, performance and job creation. While it has not yet removed investor biases toward female and racial minority entrepreneurs, equity crowdfunding has helped underrepresented entrepreneurs, who are socially and spatially distant from professional investors, gain access to capital. This research also has implications for entrepreneurs as they consider equity crowdfunding as their funding source. In particular, results highlight the relative importance of various firm and founding team characteristics among crowd investors and professional investors, which could be informative as entrepreneurs navigate the startup resource landscape.

4.7 Figures and Tables

Figure 4.1: Distribution of Amount Raised from Successful Campaigns

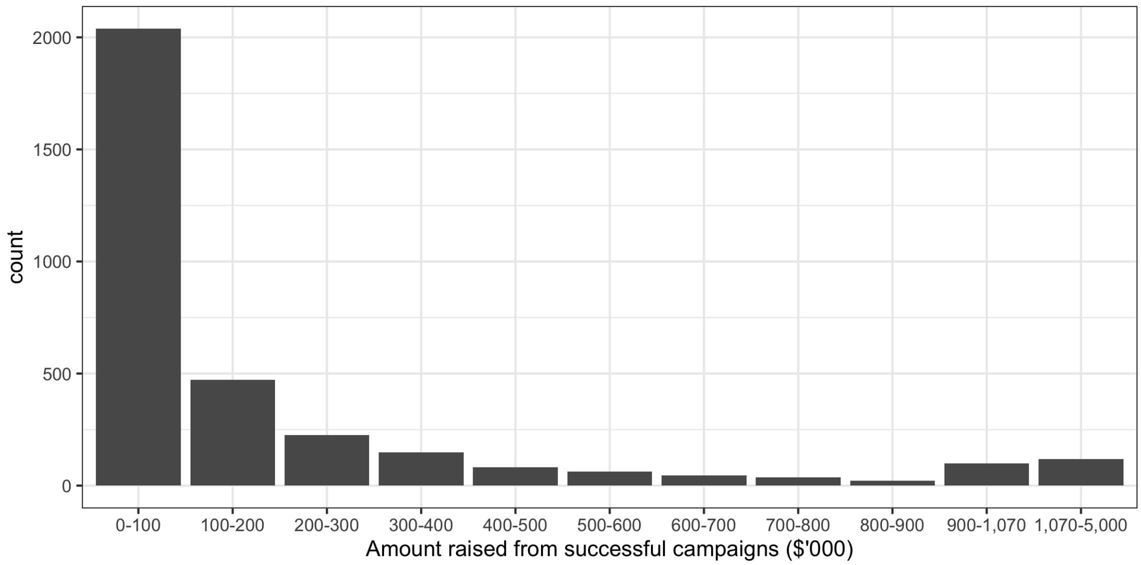


Figure 4.2: Distribution of Pre-Money Valuations of ECF Firms

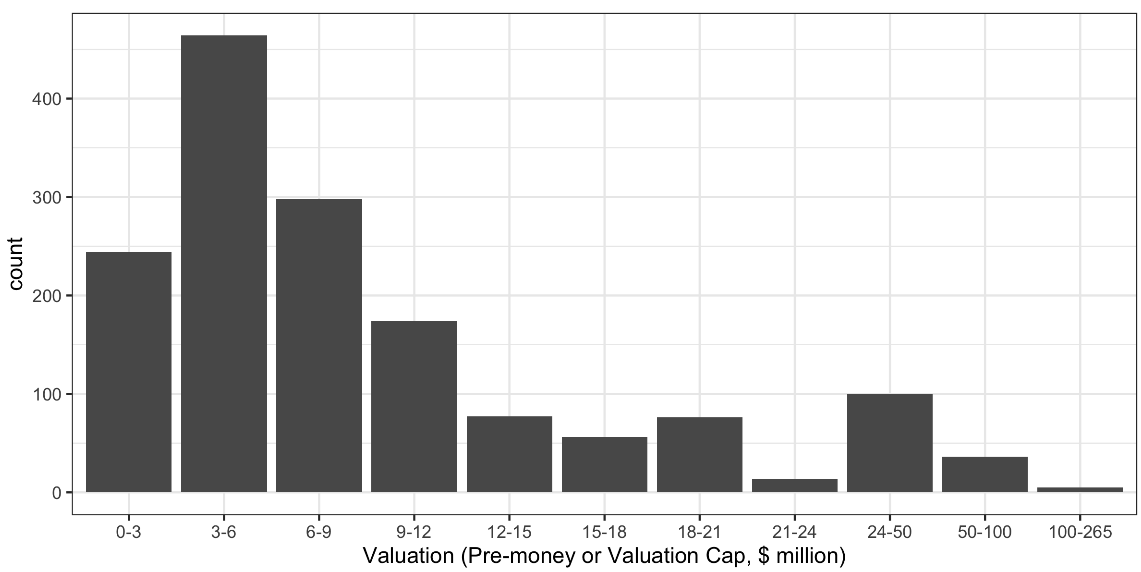
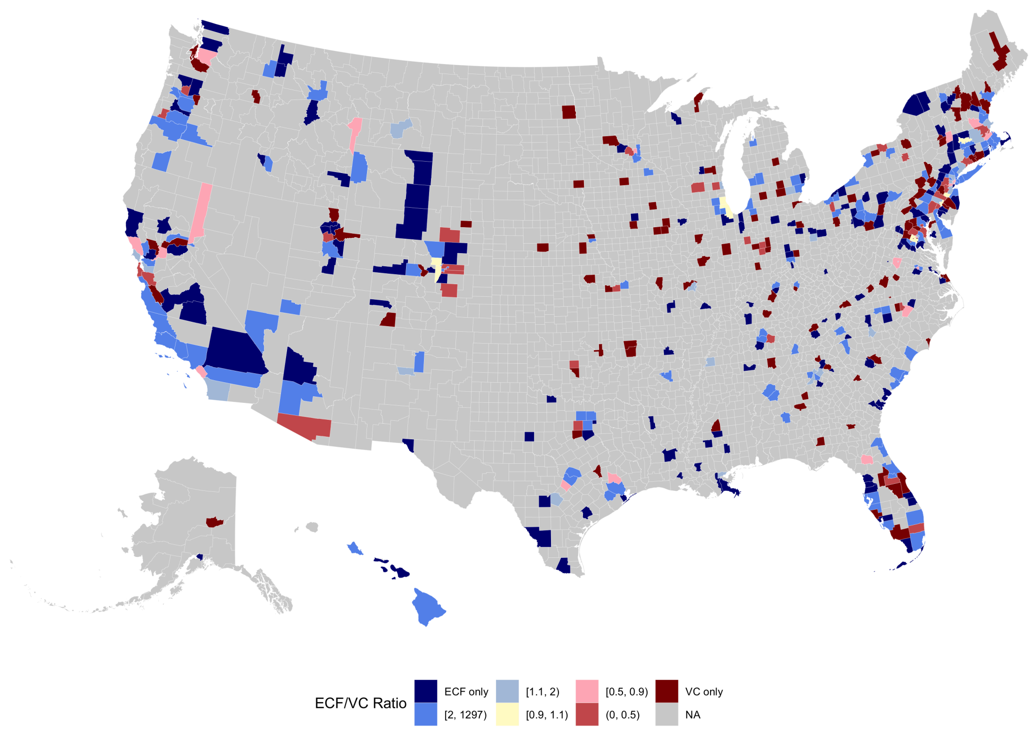


Figure 4.3: Geographic distribution of equity crowdfunding offerings and VC investments



Notes: Distributions at county-level of Regulation Crowdfunding ("ECF") offerings, VC investments, and the ratio of the amount of ECF to VC funding, 2016–2020. Increasing blue to red indicates a higher ratio of ECF to VC funding amount.

Table 4.1: Descriptive Statistics for the Sample of All ECF Firms

Statistic	N	Mean	St. Dev.	Min	Max
Offering Details					
ECF Amount	3,351	3.67	2.16	0.00	8.52
Investors	1,545	5.08	1.68	0.00	8.90
ECF Success	3,351	0.67	0.47	0.00	1.00
Target Amount	3,351	3.48	0.99	0.00	6.98
Valuation	1,544	8.63	1.54	0.00	12.48
Firm Characteristics					
Firm Age	3,351	2.92	3.74	0.00	53.00
VC Region	3,344	3.64	2.19	0.00	7.07
Team Size	3,351	1.94	1.32	1.00	15.00
Prop. Female	2,944	0.20	0.35	0.00	1.00
Prop. Asian	2,516	0.10	0.28	0.00	1.00
Prop. Hispanic	2,516	0.05	0.21	0.00	1.00
Prop. Black	2,516	0.03	0.16	0.00	1.00
Post-EC Performance					
Failure	3,351	0.09	0.28	0.00	1.00
Future Funding Received	3,351	0.03	0.18	0.00	1.00
Future Funding Amount	3,351	0.25	1.35	0.00	12.00
Following Year Prior Year Employees	712	1.62	0.94	0.00	5.65
Following Year Revenue	712	3.59	2.95	0.00	10.46
Following Year Net Income	712	0.42	1.37	−0.95	7.65
Pre-EC Performance					
Previously Received Funding	3,351	0.19	0.39	0.00	1.00
Previously Received Funding Amount	3,351	1.22	2.63	0.00	12.00
Prior Year Prior Year Employees	3,351	5.48	9.63	0.00	225.00
Prior Year Revenue	3,351	2.43	2.84	0.00	10.36
Prior Year Net Income	3,351	0.36	1.24	−3.00	8.00
Industry					
HighTech	3,308	0.38	0.48	0.00	1.00
AdvancedScience	3,308	0.07	0.26	0.00	1.00
AppPlatform	3,308	0.09	0.28	0.00	1.00
BiotechHealth	3,308	0.12	0.33	0.00	1.00
ConsumerRetail	3,308	0.45	0.50	0.00	1.00
EnergyReseourcesAgri	3,308	0.07	0.26	0.00	1.00
FinTech	3,308	0.09	0.28	0.00	1.00
Hardware	3,308	0.08	0.27	0.00	1.00
InfoTech	3,308	0.18	0.38	0.00	1.00
Manufacturing	3,308	0.04	0.20	0.00	1.00
MediaEnt	3,308	0.22	0.42	0.00	1.00
ProfServices	3,308	0.11	0.31	0.00	1.00
RealEstate	3,308	0.05	0.21	0.00	1.00
Software	3,308	0.23	0.42	0.00	1.00
OtherSector	3,308	0.06	0.25	0.00	1.00

Notes: Descriptive statistics for all 3,351 Regulation Crowdfunding offerings by 3,033 firms between May 2016 and March 2021. All variables related to amount, *Investors*, and *Employees* are logged values.

Table 4.2: Descriptive Statistics for the Sample of ECF Firms and Non-ECF Firms (from Crunchbase)

Sample:	ECF Firms					Non-ECF Firms				
Statistic:	N	Mean	St. Dev.	Min	Max	N	Mean	St. Dev.	Min	Max
ECF Success	1,630	0.68	0.46	0.00	1.00					
Funding Received	1,630	0.78	0.41	0.00	1.00	30,285	0.11	0.32	0.00	1.00
Funding Received Excl. ECF	1,630	0.13	0.33	0.00	1.00	30,285	0.11	0.32	0.00	1.00
Funding Amount	1,271	5.44	1.51	0.08	12.09	3,411	8.50	2.30	0.69	16.53
Funding Amount Excl. ECF	1,271	1.09	2.59	0.00	12.08	3,411	8.50	2.30	0.69	16.53
Funding Amount ECF Only	1,271	4.99	1.47	0.00	8.52	3,411	8.50	2.30	0.69	16.53
Previously Received Funding	1,630	0.43	0.50	0.00	1.00	30,285	0.25	0.43	0.00	1.00
Previously Received Funding Amount	1,630	2.82	3.39	0.00	11.73	30,285	1.87	3.45	0.00	17.04
Firm Age	1,630	5.65	3.79	0.00	49.00	30,285	5.81	3.26	0.00	49.00
Team Size	1,123	2.50	1.78	1.00	12.00	15,756	2.42	3.36	1.00	287.00
Founder Experience	1,123	0.26	0.44	0.00	1.00	15,756	0.24	0.43	0.00	1.00
VC Schools	1,123	0.17	0.37	0.00	1.00	15,756	0.19	0.40	0.00	1.00
Prop. Female	867	0.17	0.32	0.00	1.00	12,277	0.17	0.32	0.00	1.00
Prop. Asian	726	0.13	0.29	0.00	1.00	10,903	0.16	0.33	0.00	1.00
Prop. Black	726	0.04	0.17	0.00	1.00	10,903	0.02	0.12	0.00	1.00
Prop. Hispanic	726	0.06	0.20	0.00	1.00	10,903	0.05	0.19	0.00	1.00
VC Region	1,625	4.02	2.16	0.00	7.07	30,086	4.05	2.21	0.00	7.07
HighTech	1,630	0.60	0.49	0.00	1.00	30,285	0.49	0.50	0.00	1.00
Industry Counts	1,630	2.33	1.30	0.00	7.00	30,285	1.61	0.82	0.00	6.00

Notes: Descriptive statistics for all firm-year observations for ECF and non-ECF firms used in Table 4.5. All variables related to amount are logged values.

Table 4.3: Factors Predicting the Likelihood of Having a Crunchbase Profile

Dependent Variable:	CrunchbaseProfile	
	(1)	(2)
ECF Amount	0.034***	
	(0.004)	
ECF Success		0.132***
		(0.017)
VC Region	0.017***	0.017***
	(0.004)	(0.004)
Prior Year Employees	0.032***	0.035***
	(0.010)	(0.010)
Prior Year Revenue	0.013***	0.014***
	(0.003)	(0.003)
Valuation	0.022***	0.022***
	(0.008)	(0.008)
MissingValuation	0.199***	0.188***
	(0.067)	(0.067)
Prop. Female	−0.013	−0.020
	(0.023)	(0.023)
Prop. Asian	0.034	0.037
	(0.031)	(0.031)
Prop. Black	0.008	0.007
	(0.052)	(0.052)
Prop. Hispanic	−0.032	−0.028
	(0.042)	(0.042)
MissingDemoInfo	−0.010	−0.010
	(0.017)	(0.017)
Firm Age	0.006**	0.006**
	(0.002)	0.002)
SecurityType-Common	−0.067	−0.093
	(0.087)	(0.087)
SecurityType-Debt	−0.355***	−0.376***
	(0.089)	(0.089)
SecurityType-Limited/Non-Voting Common	−0.067	−0.086
	(0.093)	(0.093)
SecurityType-Preferred Units	−0.022	−0.032
	(0.090)	(0.091)
SecurityType-Revenue/Profit Participation	−0.310***	−0.337***
	(0.090)	(0.090)
SecurityType-SAFE	0.022	0.009
	(0.087)	(0.087)
Constant	0.214	0.256*
	(0.137)	(0.138)
Observations	3,033	3,033
R^2	0.325	0.322

Notes: The sample consists of 3,033 unique firms that participated in Regulation Crowdfunding. “Common stock” is the reference category for “Security Type.” *CrunchbaseProfile* is a binary variable indicating whether a firm is profiled on Crunchbase and thus included in the ECF sample used in Tables 4.4 to 4.8. All models include industry fixed effects and quarter fixed effects. Robust standard errors are in parentheses. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Table 4.4: Decisions to Mobilize Resources from Crowd Investors

Dependent Variable:	ECF	
	(1)	(2)
Previously Received Funding	0.042***	
	(0.004)	
Previously Received Funding Amount		0.004***
		(0.000)
Founder Experience	0.003	0.004
	(0.004)	(0.004)
VC Schools	−0.008	−0.007
	(0.005)	(0.005)
Prop. Female	0.020***	0.021***
	(0.007)	(0.007)
Prop. Asian	−0.000	0.001
	(0.007)	(0.007)
Prop. Black	0.076***	0.079***
	(0.027)	(0.027)
Prop. Hispanic	0.017	0.018
	(0.012)	(0.012)
VC Region	−0.002***	−0.002***
	(0.001)	(0.001)
Team Size	0.000	0.000
	(0.001)	(0.000)
MissingDemoInfo	0.022***	0.024***
	(0.004)	(0.004)
Firm Age	−0.001*	−0.001*
	(0.000)	(0.000)
Industry Counts	0.035***	0.036***
	(0.005)	(0.005)
Constant	−0.037***	−0.035***
	(0.008)	(0.008)
Observations	31,711	31,711
R^2	0.072	0.069

Notes: All models include industry fixed effects and year fixed effects. *ECF* is a binary variable indicating whether a firm has participated in equity crowdfunding. Robust standard errors are in parentheses. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Table 4.5: Equity Crowdfunding and Funding Outcomes

Dependent Variable:	Funding Received		Funding Amount		Funding Received Excl. ECF		Funding Amount Excl. ECF	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ECF	0.67***	0.01	−2.27***	−1.56***	0.02**	0.01	−6.18***	−1.65***
	(0.01)	(0.01)	(0.07)	(0.27)	(0.01)	(0.01)	(0.11)	(0.28)
ECF Success		0.88***		−0.75***		0.02		−4.74***
		(0.01)		(0.27)		(0.02)		(0.29)
Previously Received Funding	0.04***	0.03***	0.32***	0.32***	0.04***	0.04***	0.43***	0.41***
	(0.01)	(0.01)	(0.06)	(0.06)	(0.01)	(0.01)	(0.07)	(0.07)
Founder Experience	0.00	0.01	0.31***	0.31***	0.01	0.01	0.34***	0.31***
	(0.01)	(0.01)	(0.07)	(0.07)	(0.01)	(0.01)	(0.09)	(0.09)
VC Schools	0.05***	0.05***	0.33***	0.33***	0.05***	0.05***	0.27***	0.28***
	(0.01)	(0.01)	(0.08)	(0.08)	(0.01)	(0.01)	(0.09)	(0.09)
Prop. Female	0.03***	0.03***	0.05	0.05	0.04***	0.04***	0.20	0.23
	(0.01)	(0.01)	(0.13)	(0.13)	(0.01)	(0.01)	(0.15)	(0.15)
Prop. Asian	0.01	0.01	0.48***	0.48***	0.01	0.01	0.44**	0.43**
	(0.01)	(0.01)	(0.16)	(0.16)	(0.01)	(0.01)	(0.18)	(0.18)
Prop. Black	−0.05**	−0.03	−0.24	−0.27	−0.03	−0.03	0.16	−0.04
	(0.02)	(0.02)	(0.44)	(0.44)	(0.02)	(0.02)	(0.61)	(0.58)
Prop. Hispanic	−0.03**	−0.02*	0.41**	0.41**	−0.03*	−0.03*	0.05	0.04
	(0.01)	(0.01)	(0.19)	(0.19)	(0.01)	(0.01)	(0.24)	(0.23)
VC Region	0.00**	0.00**	0.15***	0.15***	0.00**	0.00**	0.14***	0.14***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.02)	(0.02)
Team Size	0.01**	0.01**	0.22***	0.22***	0.01**	0.01**	0.22***	0.22***
	(0.01)	(0.01)	(0.03)	(0.03)	(0.01)	(0.01)	(0.03)	(0.03)
Constant	0.23***	0.24***	6.41***	6.40***	0.24***	0.24***	6.69***	6.58***
	(0.01)	(0.01)	(0.14)	(0.14)	(0.01)	(0.01)	(0.17)	(0.16)
Observations	31,711	31,711	4,665	4,665	31,711	31,711	4,665	4,665
R^2	0.32	0.38	0.52	0.52	0.19	0.19	0.75	0.76

Notes: The sample in all models consists of all ECF and non-ECF firms. Unreported control variables are *Firm Age*, *MissingDemoInfo*, and *Industry Counts*. *Funding Received* is a binary variable indicating whether a firm has received any investment from investors, and *Funding Amount* is the logged value of the total funding amount received from any investors. *Funding Received Excl. ECF* and *Funding Amount Excl. ECF* are measured in the same way as the former variables but exclude the investments from crowd investors. All models include industry fixed effects and year fixed effects. Robust standard errors are in parentheses. Significance levels: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 4.6: Does Equity Crowdfunding Democratize Capital Access?
(Likelihood of Receiving Funding)

Dependent Variable:	Funding Received			
Empirical Approach:	Subgroup Analysis		Interaction Analysis	
Sample:	ECF	Non-ECF	All	All
	(1)	(2)	(3)	(4)
ECF			0.641^{***}	0.642^{***}
			(0.034)	(0.034)
Evidence of Quality				
Previously Received Funding	0.116^{***}	0.033^{***}	0.108^{***}	0.110^{***}
	(0.021)	(0.006)	(0.023)	(0.023)
Human Capital				
Founder Experience	−0.033	0.007	−0.048	−0.040
	(0.028)	(0.009)	(0.031)	(0.031)
VC Schools	0.008	0.055^{***}	-0.054^{*}	
	(0.030)	(0.011)	(0.033)	
University Prominence				-0.001^{*}
				(0.000)
Demographic Composition				
Prop. Female	0.002	0.036^{***}	−0.030	−0.023
	(0.049)	(0.010)	(0.051)	(0.051)
Prop. Asian	−0.003	0.006	0.010	0.014
	(0.061)	(0.011)	(0.066)	(0.066)
Prop. Black	-0.174^{***}	-0.036^{*}	−0.148	−0.143
	(0.110)	(0.020)	(0.120)	(0.120)
Prop. Hispanic	−0.110	-0.025^{*}	−0.068	−0.067
	(0.086)	(0.014)	(0.090)	(0.090)
Location				
VC Region	0.003	0.002^{**}	0.001	0.002
	(0.005)	(0.001)	(0.005)	(0.005)
Controls				
Team Size	0.021^{***}	0.011^{**}	0.008	0.008
	(0.006)	(0.006)	(0.009)	(0.008)
MissingDemoInfo	0.026	0.059^{***}	−0.037	−0.029
	(0.026)	(0.012)	(0.029)	(0.029)
Firm Age	0.001	-0.015^{***}	0.009^{***}	0.009^{***}
	(0.003)	(0.001)	(0.003)	(0.003)
Industry Counts	−0.003	−0.004	-0.023^{***}	-0.022^{***}
	(0.027)	(0.005)	(0.008)	(0.008)
Constant	0.642^{***}	0.242^{***}	0.230^{***}	0.227^{***}
	(0.072)	(0.013)	(0.013)	(0.013)
Observations	1,625	30,086	31,711	31,711
R^2	0.074	0.192	0.318	0.320

Notes: The sample in Model 1 consists of ECF firms only, and the sample in Model 2 consists of non-ECF firms only. The sample in Models 3 and 4 consists of all ECF and non-ECF firms. Each coefficient in Models 3 and 4, except for the *ECF* variable, results from the interaction effect between *ECF* and the respective variable. *Funding Received* is a binary variable indicating whether a firm has received any investment from investors. All models include industry fixed effects and year fixed effects. Robust standard errors are in parentheses. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Table 4.7: Does Equity Crowdfunding Democratize Capital Access?
(Funding Amount of Firms that Received Funding At Least Once)

Dependent Variable:	Funding Amount ECF Only			
Empirical Approach:	Subgroup Analysis		Interaction Analysis	
Sample:	ECF	Non-ECF	All	All
	(1)	(2)	(3)	(4)
ECF			−1.560***	−1.548***
			(0.184)	(0.184)
Evidence of Quality				
Previously Received Funding	0.046	0.412***	−0.315***	−0.305***
	(0.086)	(0.079)	(0.119)	(0.118)
Human Capital				
Founder Experience	0.045	0.410***	−0.362**	−0.362**
	(0.128)	(0.083)	(0.156)	(0.157)
VC Schools	0.091	0.393***	−0.365**	
	(0.127)	(0.086)	(0.157)	
University Prominence				−0.003
				(0.002)
Demographic Composition				
Prop. Female	−0.211	0.207	−0.425*	−0.436**
	(0.160)	(0.162)	(0.221)	(0.222)
Prop. Asian	0.010	0.641***	−0.578**	−0.572**
	(0.207)	(0.199)	(0.281)	(0.282)
Prop. Black	−0.202***	−1.049	0.491	0.420
	(0.555)	(0.909)	(0.407)	(0.413)
Prop. Hispanic	0.698**	0.318	0.957	0.989
	(0.326)	(0.237)	(1.048)	(1.055)
Location				
VC Region	0.012	0.201***	−0.180***	−0.182***
	(0.017)	(0.017)	(0.025)	(0.025)
Controls				
Team Size	0.084***	0.205***	−0.130***	−0.141***
	(0.030)	(0.033)	(0.046)	(0.047)
MissingDemoInfo	−0.038	0.380***	−0.455***	−0.426***
	(0.097)	(0.093)	(0.138)	(0.138)
Firm Age	0.052**	−0.006	0.031*	0.033*
	(0.010)	(0.016)	(0.017)	(0.017)
Industry Counts	−0.189*	−0.566***	−0.032	−0.022
	(0.102)	(0.120)	(0.055)	(0.055)
Constant	3.619***	6.024***	5.924***	5.902***
	(0.399)	(0.186)	(0.175)	(0.176)
Observations	1,268	3,397	4,665	4,665
R^2	0.170	0.377	0.574	0.574

Notes: The sample in Model 1 consists of ECF firms only, and the sample in Model 2 consists of non-ECF firms only. The sample in Models 3 and 4 consists of all ECF and non-ECF firms. Each coefficient in Models 3 and 4, except for the *ECF* variable, results from the interaction effect between *ECF* and the respective variable. *Funding Amount ECF Only* is the logged value of the total funding amount received from crowd investors for ECF firms and from professional investors for non-ECF firms, respectively. All models include industry fixed effects and year fixed effects. Robust standard errors are in parentheses. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Table 4.8: Democratization of Capital Access and Industry
(Likelihood of Receiving Funding)

Dependent Variable:	Funding Received			
Empirical Approach:	Subgroup Analysis			
Sample:	HighTech		Non-HighTech	
	(1)	(2)	(3)	(4)
ECF	0.651***	0.626***	0.708***	0.673***
	(0.014)	(0.032)	(0.016)	(0.035)
Evidence of Quality				
Previously Received Funding	0.016*	0.007	0.064***	0.058***
	(0.009)	(0.009)	(0.006)	(0.007)
ECF×Previously Received Funding		0.117***		0.112***
		(0.029)		(0.031)
Human Capital				
Founder Experience	0.007	0.009	0.002	0.006
	(0.012)	(0.012)	(0.009)	(0.009)
VC Schools	0.071***	0.077***	0.024**	0.021*
	(0.015)	(0.015)	(0.011)	(0.011)
ECF×Founder Experience		−0.039		−0.087*
		(0.033)		(0.051)
ECF×VC Schools		−0.087**		0.044
		(0.041)		(0.045)
Demographic Composition				
Prop. Female	0.034**	0.040**	0.038***	0.038***
	(0.017)	(0.017)	(0.011)	(0.011)
Prop. Asian	0.024	0.025	0.001	−0.003
	(0.016)	(0.016)	(0.013)	(0.013)
Prop. Black	−0.025	−0.029	−0.069**	−0.036
	(0.033)	(0.031)	(0.031)	(0.026)
Prop. Hispanic	−0.033	−0.039*	−0.031*	−0.018
	(0.023)	(0.023)	(0.017)	(0.016)
ECF×Prop. Female		−0.101		0.004
		(0.084)		(0.061)
ECF×Prop. Asian		−0.020		0.033
		(0.096)		(0.085)
ECF×Prop. Black		0.033		−0.304**
		(0.147)		(0.154)
ECF×Prop. Hispanic		0.092		−0.332**
		(0.105)		(0.156)
Location				
VC Region	0.004***	0.004***	−0.000	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)
ECF×VC Region		−0.001		0.002
		(0.006)		(0.008)
Controls				
Team Size	0.011	0.011	0.012***	0.012***
	(0.007)	(0.007)	(0.003)	(0.003)
MissingDemoInfo	0.077***	0.078***	0.031***	0.031***
	(0.016)	(0.016)	(0.008)	(0.008)
Firm Age	−0.021***	−0.021***	−0.007***	−0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Industry Counts	−0.034***	−0.035***	−0.007	−0.008
	(0.006)	(0.006)	(0.008)	(0.008)
Constant	0.363***	0.364***	0.113***	0.116***
	(0.020)	(0.020)	(0.015)	(0.015)
Observations	15,754	15,754	15,957	15,957
R^2	0.323	0.325	0.295	0.297

Notes: The sample in Models 1 and 2 consists of all ECF and non-ECF firms in high-technology industries, and the sample in Models 3 and 4 consists of all ECF and non-ECF firms in non-high-technology industries. *Funding Received* is a binary variable indicating whether a firm has received any investment from investors. All models include industry fixed effects and year fixed effects. Robust standard errors are in parentheses. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Table 4.9: How Does Equity Crowdfunding Affect Future Performance?

Sample:			ECF		
Dependent Variable:	Failure	Future Funding Received	Employees	Following Year Revenue	Net Income
	(1)	(2)	(3)	(4)	(5)
Panel A					
ECF Success	−0.091***	0.023***	−0.001	0.436	0.130
	(0.011)	(0.007)	(0.150)	(0.418)	(0.337)
Valuation	−0.003	0.003	−0.011	0.024	0.080
	(0.004)	(0.003)	(0.027)	(0.075)	(0.060)
Missing Valuation	−0.008	0.019	−0.149	−0.048	0.716
	(0.040)	(0.027)	(0.244)	(0.678)	(0.544)
Firm Age	−0.004***	−0.002**	0.003	−0.034*	0.017
	(0.001)	(0.001)	(0.006)	(0.019)	(0.014)
Prior Year Employees			0.805***		
			(0.028)		
Prior Year Revenue				0.817***	
				(0.025)	
Prior Year Net Income					0.147***
					(0.043)
Constant	0.212***	0.155***	0.674**	0.763	−0.849
	(0.061)	(0.041)	(0.330)	(0.926)	(0.743)
Observations	3,200	3,200	710	710	710
R^2	0.095	0.072	0.619	0.696	0.068
Panel B					
ECF Amount	−0.018***	0.005***	0.047***	0.073	0.073*
	(0.002)	(0.001)	(0.017)	(0.049)	(0.039)
Valuation	−0.001	0.002	−0.018	0.012	0.067
	(0.004)	(0.003)	(0.027)	(0.075)	(0.060)
Missing Valuation	−0.003	0.016	−0.197	−0.123	0.627
	(0.040)	(0.027)	(0.244)	(0.678)	(0.544)
Firm Age	−0.004***	−0.002***	0.002	−0.034*	0.015
	(0.001)	(0.001)	(0.006)	(0.019)	(0.014)
Prior Year Employees			0.798***		
			(0.027)		
Prior Year Revenue				0.812***	
				(0.026)	
Prior Year Net Income					0.146***
					(0.043)
Constant	0.204***	0.157***	0.473	0.880	−1.025
	(0.060)	(0.041)	(0.300)	(0.850)	(0.678)
Observations	3,200	3,200	710	710	710
R^2	0.097	0.073	0.623	0.697	0.073

Notes: The sample consists of ECF firms that participated in equity crowdfunding between May 2016 and December 2020. Panel A explores whether having a successful crowdfunding campaign by meeting the minimum target amount (*ECF Success*) is associated with the measures of future performance; Panel B explores how the amount received from crowd investors (*ECF Amount*) is associated with the measures of future performance. *Failure* indicates whether a firm has failed; *Future Funding Received* indicates whether a firm has received subsequent funding from professional investors; *Following Year Employees*, *Revenue*, and *Net Income* measure the employee size, revenue, and net income from the fiscal year following the ECF date. All models include industry fixed effects and quarter fixed effects. Robust standard errors are in parentheses. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Chapter 5

Conclusion and Directions for Future Research

Scholars and popular press often describe innovation as driven by technology, product, or the company itself. Therefore the lion's share of research has examined innovation processes and outcomes at the firm level. Yet the members of an organization are the ones who bring in new ideas and knowledge to the firms triggering the emergence of new technology and driving innovation. To better understand how innovation-driven firms manage entrepreneurial and innovative human capital and how to improve their organizational outcomes through these individuals, I study the mobility and resource exchange dynamics of entrepreneurs and innovators.

The three essays of my dissertation address questions related to hiring and funding processes of entrepreneurs and innovators. In the first essay, I explore how performances of external hires and their teams are affected by mobility and how team design affects the innovation performance of both groups. I tackle two important challenges faced by managers—hiring and organizing human capital—in gaining competitive advantage through knowledge production. This study contributes to research on mobility and innovation by providing a more nuanced description of how firms can assess the value of external hiring. My study suggests that it is integral to look beyond the performance implications of new hires and jointly consider how other employees are affected. The diverging pattern of teammates' quantity and quality of innovation performance suggests that managers should carefully consider their immediate strategic or performance goals when devising recruiting strategies. Also, by investigating the role of team design, I propose effective "integration strategies" previously overlooked by scholars.

In the second essay, we explore how innovation-driven organizations evaluate former entrepreneurs. Our results highlight that fit and commitment, rather than capability and human capital, are the dominant organizational perspectives related to how hiring firms evaluate entrepreneurial human capital. These findings deepen our understanding of organizations' human capital strategies and individuals' career trajectories. While scholars have focused on examining the organizational spawning process, or the outflow of human capital from established firms to entrepreneurial ventures, we build on this research by examining the reverse process, or the inflow of entrepreneurs into established firms.

By examining career mobility and hiring at innovation-driven firms, the first two essays build on interorganizational mobility and human capital research. There are many avenues that future work can explore. The first fruitful direction, building on my first essay, is to understand whether the benefits of external hiring offset the costs. While I explored how external hiring could bring knowledge benefits, it is difficult to conduct a cost-benefit analysis without collecting compensation information of employees. It would be interesting to compare how much a recruited innovator contributes to the firm and the associated costs of hiring by collecting compensation information. Another avenue for future research, born out of the second essay, is to unpack what types of firms entrepreneurs choose to apply after their founder experience. In other future projects, I plan to investigate this line of inquiry by investigating the value of early hires and strategies to efficiently manage them from the perspectives of early-stage startups, not just established firms.

Studying the hiring of entrepreneurial and innovative human capital in the first two essays inspired me to study how the human capital of entrepreneurs and investors influences early-stage venture outcomes. In the third essay, I examine whether the expertise of investors shapes how they assess ventures and whether allowing the general public to invest in startups could help reduce structural barriers faced by underrepresented entrepreneurs. While prior literature has largely focused on how the resource demand-side characteristics (startups, founding teams) affect funding outcomes, this essay shows how the human capital of investors could determine resource allocation to startups. Also, the findings contribute to our knowledge about resource mobilization in entrepreneurship, as well as research examining the growing role of crowds in affecting organizational outcomes.

Many questions remain to be answered. What are the long-term consequences of securing funding from non-expert crowds rather than professional experts? How do the background and experience of entrepreneurs affect how they perceive the market value of their own firms and, in turn, how investors react to these valuation amounts when reviewing startup investment opportunities? What are the other important supply-side dimensions (e.g., socioeconomic status, career experience) that could affect research allocation to startups? Why do the status-based biases persist among crowd investors? I plan to unpack the mechanisms that drive persistent gender and racial biases. Also, it would be important to come up with intervention strategies that could reduce status-based biases among investors, regardless of their expertise.

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