# Can Early-Stage Startups Hire Talented Scientists and Engineers? Ability, Preferences, and Employee Job Choice

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**ABSTRACT**

Early-stage technology startups rely critically on talented scientists and engineers to commercialize new technologies. And yet, they compete with large technology firms to hire the best workers. Theories of ability sorting predict that high ability workers will choose jobs in established firms that offer greater complementary assets and higher pay, leaving low ability workers to take lower-paying and riskier jobs in startups. We propose an alternative view in which heterogeneity in both worker ability and preferences enable startups to hire talented workers who have a taste for a startup environment, even at lower pay. Using a longitudinal survey that follows 2,394 science and engineering PhDs from graduate school into industrial employment, we overcome common empirical challenges by observing ability and stated preferences prior to first-time employment. We find that both ability and career preferences strongly predict startup employment, with high ability workers who prefer startup employment being the most likely to work in a startup. We show that this is due in part to the dual selection effects of worker preferences resulting in a large pool of startup job applicants, and startups "cherry picking" the most talented workers to make job offers to. Additional analyses confirm that startup employees earn approximately 17% lower pay. This gap is greatest for high ability workers and persists over workers' early careers, suggesting that they accept a negative compensating differential in exchange for the non-pecuniary benefits of startup employment. This is further supported by data on job attributes and stated reasons for job choice.

*Keywords*: Startup early employees, technology entrepreneurship, human capital, job choice, scientists and engineers

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## 1 Introduction

*"Talented people don't need to work for you; they have plenty of options. You should ask yourself a more pointed question: Why would someone join your company as its 20th engineer when she could work at Google for more money and more prestige?*"– Peter Thiel (2014) *Zero to One*

Technology startups play a key role in innovation, economic development, and job creation. While prior entrepreneurship research has focused on understanding founders, less attention has been paid to those who join founders as early employees (Ouimet and Zarutskie 2014, Roach and Sauermann 2015, Sorenson et al. 2021). Early-stage technology startups rely critically on talented scientists and engineers to commercialize new technologies (Baron et al. 1996, Hsu 2009), and yet these startups may be disadvantaged relative to established firms in the market for talented workers. Not only do established firms offer higher pay, greater job security, and other benefits such as on-the-job training relative to early-stage startups (Oi and Idson 1999, Sørensen 2007, Bidwell and Briscoe 2010, Ouimet and Zarutskie 2014, Dahl and Klepper 2015, Burton et al. 2018), but they also offer greater complementary assets such as research tools, materials, and other talented workers that increase R&D employees' productivity (Arora and Gambardella 1994, Agarwal and Ohyama 2013, Dahl and Klepper 2015). As such, early-stage startups may struggle to hire high ability workers, possibly constraining their growth and success (Beckman and Burton 2008, Agarwal et al. 2016, Honoré and Ganco 2021).

The existing empirical evidence on startup human capital provides an unclear picture. On the one hand, research shows that employees in small and young firms are paid less than their established firm counterparts, which is often interpreted as evidence of lower quality human capital (Brown and Medoff 1989, Oi and Idson 1999, Brown and Medoff 2003, Haltiwanger et al. 2013, Ouimet and Zarutskie 2014, Burton et al. 2018, Babina et al. 2019, Sorenson et al. 2021). On the other hand, high-growth VC-backed ventures have been shown to hire talented workers by offering attractive workplace benefits, higher wages, and startup equity (Bengtsson and Hand 2013, Kim 2018). However, well-funded high-growth ventures differ markedly from early-stage startups, which typically face severe resource constraints and greater uncertainty in their potential success. Thus, it remains an open question whether and why talented scientists and engineers would join startups as early employees when they have seemingly better options in established firms.

We argue that a deeper understanding of startup human capital requires attention to not only ability and wages, but also to differences in workers' career preferences for employment in different types of firms. Indeed, recent evidence suggests that a meaningful share of prospective employees have a distinct taste for joining startups as non-founding employees based in part on the unique job attributes that startups offer relative to established firms (Roach and Sauermann 2015). Such heterogeneity in preferences may enable startups to attract high ability "startup types", even at lower pay (Stern 2004). Perhaps more importantly, we also consider the roles of ability and preferences together, which suggests that high ability startup types face a particularly strong trade-off between the productivity benefits of working in an established firm and the preference benefits of working in a startup. This trade-off implies that if high ability startup types perceive the non-pecuniary benefits in startups to exceed the opportunity costs of forgoing the productivity benefits of established firms, then startups may be able to hire high ability workers despite offering lower pay. Such a taste-based compensating differential also implies that interpreting wages as a proxy for ability will systematically under-estimate startups' human capital.

The empirical challenge with studying workers' transitions into startup employment is that the determinants of employment outcomes are often unobservable to researchers. In addition, given that individuals' ability and preferences may be influenced over time and in different ways by their employment setting, observing workers' transition from one job to another complicates researchers' efforts to tease apart selection and treatment effects (Sørensen 2007, Elfenbein et al. 2010). We overcome these challenges through a longitudinal survey that follows a cohort of 2,394 science and engineering PhDs who were first surveyed as students in U.S. research universities and then again in their first-time employment in industrial research and development (R&D). We supplement the survey with LinkedIn data to obtain comprehensive career profiles on all survey respondents. A key advantage of our survey research design is that it provides direct measures of workers' typically unobserved career preferences, along with detailed university department rankings to proxy for ability. Moreover, by observing individuals several years prior to their first employment, we can examine selection prior to organizational treatment effects. We further disentangle the roles of ability and preferences through survey responses on startup job applications and job offers, starting earnings, and job characteristics.

We find that higher ability workers are more likely to work in early-stage startups, even though they earn significantly less than their observationally equivalent counterparts in established firms. Moreover, we observe strong employee self-selection into startups based on ex ante career preferences. Considering both ability and preferences jointly yields a more complete picture: despite facing a greater trade-off between productivity and preference benefits, high ability startup types are the most likely to work in a startup. This suggests that the preference benefits of startup employment outweigh the costs of forgoing greater productivity and higher pay in established firms. Supporting this interpretation, we show that startup employees earn approximately 17% less starting pay than their established firm peers and this gap persists for several years over their early careers. These patterns indicate that the lower earnings of startup employees reflect in part a taste-based compensating differential rather than lower ability. Finally, we also show that ability and preferences play different roles at different stages of the job search process: workers apply to startups based on their career preferences and startups select workers based on ability. Together these results suggest that preference-based self-selection creates a sizeable pool of startup job applicants, which in turn allows startups to "cherry pick" the most talented workers as early employees.

Our study contributes to several streams of the entrepreneurship literature. First, we contribute to a growing body of research seeking to understand startup human capital (Haltiwanger et al. 2013, Ouimet and Zarutskie 2014, Agarwal et al. 2016, Burton et al. 2018, Kim 2018, Babina et al. 2019, Sorenson et al. 2021). This work has largely examined the relationship between firm size or age and employee wages, often interpreting lower wages as evidence of lower human capital. We advance this work by observing ability and preferences separately prior to first-time employment, allowing us to tease apart ability and preference effects. Moreover, we integrate prior work that has focused on either ability or preferences to consider how they together shape startups' access to human capital. Considering ability and preferences jointly using direct measures allows us to examine whether lower wages in startup employment reflect lower human capital or a compensating differential, and we find evidence for the latter. Finally, prior work has compared firms across levels of size or age (Brown and Medoff 1989, Haltiwanger et al. 2013, Ouimet and Zarutskie 2014, Babina et al. 2019, Sorenson et al. 2021) or growth-stage VC-backed ventures versus established firms (Bengtsson and Hand 2013, Kim 2018). We argue that early-stage technology startups have unique characteristics – and face unique challenges – that deserve study in their own right (Hsu 2009).

Second, a large body of entrepreneurship research has studied how ability or preferences explain entry into entrepreneurship as a founder. For example, studies suggest that high ability individuals are more likely to transition to entrepreneurship in part because they can generate higher financial returns to their ability through residual claimancy (Jovanovic 1979, Elfenbein et al. 2010, Åstebro et al. 2011, Braguinsky et al. 2012, Hegde and Tumlinson 2021). Other studies show that individuals with preferences for autonomy, risk, and task variety realize non-pecuniary benefits from becoming an entrepreneur that may offset lower earnings than in wage employment (Kihlstrom and Laffont 1979, Evans and Leighton 1989, Hamilton 2000, Lazear 2005, Elfenbein et al. 2010, Åstebro et al. 2011). We extend this work to an under-studied entrepreneurial actor: early-stage employees who join founders in their entrepreneurial efforts. In doing so, we demonstrate how studying ability and preferences jointly can yield novel insights, suggesting opportunities for future research to consider both aspects when studying decisions to become an entrepreneur and employment choice more broadly.

Third, entrepreneurship scholars show great interest in whether and how organizational characteristics shape employees' subsequent founding decisions (Burton et al. 2002, Stuart and Ding 2006, Sørensen 2007, Elfenbein et al. 2010). A related emerging stream of research takes a "careers perspective" (Burton et al. 2016), showing that early employment experiences in different types of firms can have long-lasting implications for future entrepreneurship (Burton et al. 2002, Hsu et al. 2007, Elfenbein et al. 2010). We complement this work by studying how workers sort into different types of organizations to begin with, focusing on recent graduates who still have long careers ahead of them. We find significant selection with respect to ability and preferences, including founder types who sort into startups to learn or acquire skills that can facilitate future founding (Sørensen 2007). As such, our results suggest the importance of accounting for employee selection when studying organizational treatment effects. More importantly, rather than studying selection and treatment in isolation, there may be value in considering them jointly. For example, it is likely that employees with different levels of pre-existing entrepreneurial interests respond differently to "treatments" such as social influence, the arrival of entrepreneurial opportunities, or co-workers' offers to join a new venture (Roach and Sauermann 2015, Shah et al. 2019).

Finally, our results contribute to the more general literature on employee sorting and labor market matching. Although much of this literature focuses on the sorting of high ability workers into high quality firms (Becker 1973, Eeckhout 2018), recent work has shown that high ability workers may also sort into low quality firms in exchange for higher pay (Bhaskarabhatla et al. 2021). We provide evidence on an alternative mechanism, where high ability workers take jobs in resource-constrained firms at lower pay in exchange for the non-pecuniary benefits unique to those firms (see Stern 2004, Sorkin 2018). Our results suggest promising avenues for future research to incorporate heterogeneity in workers' preferences into theories of labor market matching.

## 2 Conceptual Framework

We begin by outlining differences in job characteristics between startups and established firms, as well as differences in the types of workers these firms seek to hire (§2.1). Next, we draw upon ability-based theories to explain the prevailing view that high ability workers will choose jobs in established firms where they expect to be more productive and to earn higher pay, leaving low ability workers to take jobs in startups (§2.2). We then incorporate preference-based theories to argue that workers – including high ability – may choose to work in early-stage startups due to their preferences for non-pecuniary job attributes, even at lower pay (§2.3). Considering heterogeneity in *both* ability and preferences implies that high ability workers with a taste for startup employment face a trade-off between the preference benefits from working in their desired work environment and the opportunity costs of lower productivity and lower wages by forgoing employment in an established firm. On the other hand, ability and preferences are reinforcing for high ability workers with a preference for working in an established firm (§2.4). We also consider the role of labor demand, concluding that startups' opportunities to hire talented workers depend on the strength of the preference-productivity trade-off for high ability startup types (§2.5).

Although selection into startups is of interest at all career stages, we focus on novice employees transitioning to their first industry job. Focusing on first-time employment provides advantages in terms of both conceptual development and empirical analysis. In particular, it allows us to abstract away from potential confounding effects of work experience and organizational influence that are more salient when examining job mobility at later career stages (Burton et al. 2002, Elfenbein et al. 2010). Similarly, studies of job choice later in the career face the challenge that mobility is often endogenous since those who leave their employers may be selected on unobserved characteristics. This selection problem is less relevant for new graduates, all of whom must make a first-time employment decision after graduation.

### 2.1 Employment in Early-Stage Technology Startups

We conceptualize early-stage technology startups as small young firms founded to commercialize emerging technologies. As such, our focus is on early employees hired by new firms rather than the later hires in more mature VC-backed ventures often considered in prior work.[1] In the following, we highlight three aspects of startups and established firms that are particularly relevant for our discussion of job choice and employment outcomes: the nature of the work and the resulting demand for talented workers, the availability of resources, and differences in other job attributes. By focusing on key differences between R&D-intensive early-stage startups and established firms, we abstract away from heterogeneity among different startups or different established firms. In addition, we assume that established firm employment is the conventional career path for recent graduates, while working in a startup is the less common alternative (National Science Board 2014).

First, the primary activity of early-stage technology startups is the commercialization of new technologies that are often at the cutting-edge of their field. Consider, for example, the growing number of startups in areas such as artificial intelligence, biotechnology, alternative energy, and robotics. Given their focus on technology commercialization, such startups require talented scientists and engineers as early employees to increase their chances of technological success (Andersson et al. 2009). In contrast, established technology firms have portfolios of R&D projects that include both innovative projects to commercialize cutting-edge technologies as well as incremental projects to sustain existing technologies (Cohen and Klepper 1996). For example, firms such as Amazon, Google and Microsoft have projects at the technological frontiers of AI and robotics, as well as projects that focus on incremental improvements to technologies in their existing lines of business. This has important implications for the types of employees that startups and established firms seek to hire: While startups need high ability scientists and

[1] VC-backed ventures have reduced much of their technological and market uncertainty, allowing them to attract higher levels of funding to support growth. As such, they possess the resources to pay higher salaries (Kim 2018) to compete aggressively to lure away top talent from established firms.

engineers, large established firms employ both higher ability employees to work on cutting-edge projects and lower ability employees to work on incremental projects.

Second, early-stage startups face severe resource constraints relative to established firms (Evans and Leighton 1989, Hsu 2007, Agarwal and Ohyama 2013). These constraints make it difficult for them to invest in the complementary assets that employees need to successfully commercialize new technologies, such as advanced research lab infrastructure or computational equipment. Resource constraints also make it difficult to offer competitive salaries (Hsu 2009) and to attract complementary human capital that high ability employees often need to increase their productivity (Bhaskarabhatla et al. 2021).

Finally, early-stage startups differ from established firms with respect to various job attributes associated with their small size and young age. For example, startups tend to have flat hierarchies and low levels of bureaucracy, providing employees with considerable autonomy and task variety (Lazear 2005, Sørensen 2007, Elfenbein et al. 2010). Startup employment may also offer aspiring founders opportunities to develop skills and experience that are beneficial to future transitions to entrepreneurship (Gompers et al. 2005, Sørensen 2007, Elfenbein et al. 2010). Moreover, as startups grow and achieve success they may offer early employees opportunities for rapid career advancement (Neff 2012, Sorenson et al. 2021). Large established firms, on the other hand, tend to have greater bureaucracy and routinized organizational practices (Sørensen 2007) with formalized career ladders within specialized functional roles (Baron et al. 1996, Sørensen 2007, Cappelli 2008, Bidwell and Briscoe 2010). At the same time, established firms offer benefits typically unavailable in startups such as on-the-job training and other skill-development programs that can be particularly attractive to early-career workers (Bidwell and Briscoe 2010). Finally, established firms offer greater job security, while startup employees face greater risk due to uncertainty about their employers' success (Hsu 2009, Neff 2012, Sorenson et al. 2021).[2]

Building on this discussion of differences between jobs in early-stage technology startups and established technology firms, we next employee job choice to consider the potential role of ability and preferences in shaping individuals' decisions to seek employment in startups.

### 2.2 Ability and Startup Job Choice

A prominent stream of research in economics and strategy considers how employees of varying ability sort into firms of varying quality (Becker 1973, Agarwal and Ohyama 2013, Eeckhout 2018). A central insight of this research is that income maximizing high ability workers will choose jobs in firms that have greater resources to both invest in complementary assets that increase their productivity and to offer them

[2] Although graduates with advanced technical skills are likely to have other employment opportunities if a startup fails, survey evidence confirms that PhDs see job risk as a major disadvantage of startup employment (Roach and Sauermann 2010).

higher pay through rent sharing.[3] In the context of R&D, such complementary assets include physical R&D infrastructure and research tools, as well as other talented workers. Given that early-stage startups typically lack the financial resources to invest in such complementary assets and to offer pay comparable to established firms, high ability workers will instead be more attracted to jobs in established firms.

Although the literature commonly focuses on physical and human capital as complementary assets, complementarities may also arise between workers' ability and the nature of their work. As discussed above, cutting-edge R&D projects are more challenging and more likely to be successful if performed by high ability workers (Andersson et al. 2009). Similarly, high ability scientists and engineers may expect to be more productive working on cutting-edge R&D projects rather than incremental projects. Given that early-stage technology startups are typically founded to commercialize novel discoveries at the frontier of science and technology (Gans and Stern 2003, Hsu 2009), high ability worker may find startup employment particularly attractive. At the same time, established firms also offer opportunities to work on cutting-edge R&D projects in addition to greater complementary assets and higher pay. As such, high ability workers should still find jobs in established firms more attractive than in startups.

Recent research, however, suggests that high ability workers don't always work in higher quality firms. In particular, Bhaskarabhatla et al. (2021) find that high ability inventors move to firms with lower innovative capabilities for higher pay. Applied to our context, this suggests that high ability workers might choose jobs in early-stage startups with lower complementarities if offered higher pay than they could earn in an established firm. Although there is evidence that later-stage VC-backed firms can attract high ability workers by paying higher wages (Kim 2018), resource-constrained early-stage startups are likely unable to offer such a wage premium.

Of course, resource-constrained startups may offer equity instead of higher pay (Hand 2008). Indeed, the entrepreneurship literature has emphasized expectations of future financial payoffs in explaining the transition of high ability individuals from wage employment to entrepreneurship (Åstebro et al. 2011, Braguinsky et al. 2012, Hegde and Tumlinson 2021). Given the large disparity between founder and employee equity shares, however, startup employees can expect much smaller financial payoffs if the venture is successful. Consistent with this, Aran & Murciano-Goroff (2021) show through a recent survey of U.S. workers with STEM degrees that only 10% viewed startup equity primarily as financial compensation. Instead, 30% viewed it as equivalent to a lottery ticket and 25% as an incentive alignment

[3] An important body of research in labor economics studies the "positive assortative matching" of high ability workers with other high ability workers or high quality firms (Becker 1973). We draw upon this literature to guide our discussion of how high ability workers might choose between jobs in startups or established firms (i.e., focusing on the supply-side). Our discussion and empirical findings also speak to "negative assortative matching", whereby high ability workers match with lower quality firms (Eeckhout 2018). We thank the Associate Editor and two reviewers for suggesting these connections.

mechanism, drawing into question the role of equity as a key driver of the decision to work in a startup. Moreover, given the low probability of a successful exit, the realized value of startup equity in most instances is zero.[4] At the same time, stock options are also offered by many publicly traded technology companies based on a known share price, making them more valuable to most workers. Thus, while equity may be necessary for any worker to accept a startup job, it is likely insufficient to lure high ability workers away from the higher pay and attractive stock options available in established firms.

Taken together, this discussion suggests that high ability workers who seek to maximize their productivity and income are unlikely to take jobs in resource-constrained startups over jobs in established firms. However, as argued above, early-stage startups differ from established firms in not only resources and income, but also with respect to non-pecuniary job attributes that may be particularly attractive to certain types of workers, including many with high ability.

### 2.3 Career Preferences and Startup Job Choice

Going beyond the assumption of income maximization, a rich literature has explored the role of individuals' preferences for non-pecuniary benefits in shaping job and career choices. This literature argues that some workers are willing to accept lower pay for jobs that offer desired attributes such as freedom, intellectual challenge, or security (Rosen 1986). For example, Stern (2004) shows that R&D jobs that offer non-financial aspects that scientists value such as autonomy and opportunities to publish also pay lower salaries, concluding that "scientists pay to be scientists". Although this work often assumes homogenous preferences, other studies highlight that individuals vary in the degree to which they value certain non-pecuniary benefits over than others (Elfenbein et al. 2010, Agarwal and Ohyama 2013, Sauermann and Roach 2014). This heterogeneity, in turn, suggests that workers may select into different types of firms or careers due in part to their individual preferences for specific job attributes.

While we study startup employment and not founding, the entrepreneurship literature offers guidance on how preferences can be conceptualized. Much of the literature focuses on preferences for specific job attributes such as autonomy (Evans and Leighton 1989), risk (Kihlstrom and Laffont 1979), or task variety (Lazear 2005, Åstebro et al. 2011). Other theories consider a "taste" for a specific employment setting (e.g., "taste for entrepreneurship") that involves bundles of job attributes (Stern 2004, Elfenbein et al. 2010, Roach and Sauermann 2015). We build on Roach & Sauermann (2015), who link the two levels to understand individuals' career preferences for becoming a founder ("*founder types*"), joining a startup

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[4] While data on startup employee earnings and equity are exceptionally rare, a media report using AngelList data estimated that the average early-stage startup employee does not earn more the average established firm employee when taking into account the low rate of successful startup exists and employee equity stakes: https://80000hours.org/2015/10/startup-salaries-and-equity-compensation

as an employee with no intention of becoming a founder ("*joiner types*") or working in an established firm ("*established firm types*").[5] We expand upon their ideas within the context of scientists and engineers choosing between R&D jobs in early-stage technology startups versus established technology firms.

First, "founder types" are individuals who aspire to become entrepreneurs in the future. Founder types are characterized by preferences for job attributes that align with entrepreneurship such as autonomy, risk, or performing a variety of tasks (Kihlstrom and Laffont 1979, Evans and Leighton 1989, Lazear 2005, Åstebro and Thompson 2011).[6] Since most aspiring founders lack an entrepreneurial opportunity at the beginning of their careers (Shane 2000), they will first seek employment rather than found their own firm. Indeed, studies have shown that most founders transition to entrepreneurship from wage employment (Burton et al. 2002).[7] Working in a startup may also enable founder types to acquire additional skills and knowledge that will better prepare them to start their own company in the future (Gompers et al. 2005, Sørensen 2007, Elfenbein et al. 2010).

Second, many individuals are attracted to joining a startup as an employee but have little interest in becoming a founder themselves (Roach and Sauermann 2015). Such "joiner types" share with founder types preferences for certain job attributes such as autonomy and risk, but also differ in meaningful ways that make their career preference unique. For example, joiner types may be attracted to working in a small firm that enables them to directly contribute to a venture's success but may not wish to bear the greater responsibility that comes with being a founder. Joiner types may also prefer to work in a startup out of an interest in commercialization work activities rather than the managerial activities required of founders (Elfenbein et al. 2010). At the same time, startups may offer employees opportunities to work on a broader range of commercialization activities relative to more specialized R&D positions in established firms (Lazear 2005, Elfenbein et al. 2010). In addition, some scientists and engineers may find startups attractive because they can work on cutting-edge R&D projects that offer not only greater productivity (see above) but also intrinsic rewards such as intellectual challenge and job satisfaction (Stern 2004, Roach and Sauermann 2015, Bhaskarabhatla et al. 2021).

In contrast to founder and joiner types who are both attracted to working in a startup, others prefer to work in an established firm. These "established firm types" have career preference that reflect in part a

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[5] Roach & Sauermann (2015) considered entrepreneurial preferences in an absolute sense (i.e. interest in a particular career above a certain level, independent of interest in other careers). Since we examine the relationship between preferences and job choice, we use a relative conceptualization of preferences.

[6] Although we focus on preferences for different job attributes, career preferences may be shaped by social influences such as departmental norms regarding entrepreneurship or founder role models (Stuart and Ding 2006, Roach and Sauermann 2015, Azoulay et al. 2017), as well as individuals' "identity" with different occupations (Akerlof and Kranton 2000).

[7] In our survey data, among industry PhDs who aspired to become an entrepreneur during graduate school, 19% founded a startup after graduation and 81% worked in other firms.

desire for job security (Kihlstrom and Laffont 1979, Halaby 2003), well-defined job roles and career ladders (Cappelli 2008, Bidwell and Briscoe 2010), and greater organizational structure and formalization (Halaby 2003). They may also value other benefits offered by established firms such as on-the-job training (Bidwell and Briscoe 2010) and organizational prestige (Burton et al. 2002, Bidwell et al. 2015). With respect to work activities, some established firm types may be attracted to cutting-edge R&D projects in large innovative firms (e.g., Google DeepMind and Amazon MARS), while others may prefer to work on more incremental R&D projects that are less demanding and more certain in their outcomes.

Although we make no assumptions about the long-term stability of individuals' career preferences, we contend that preferences expressed prior to entry into the labor market will shape which jobs individuals apply to and which job offers they accept if given the choice.[8] More specifically, founder and joiner types will be more likely to seek employment in startups than established firm types, while the latter will be more likely to seek employment in established firms. Of course, even founder and joiner types will not accept any startup job regardless of the startup's potential quality, as the benefits offered by lower quality startups may not be sufficient.[9] Thus, while founder and joiner types may most prefer to work in a startup with the potential for success, they are likely to turn down offers from low quality startups to instead work in an established firm.[10] This discussion leads us to now consider more explicitly how employment outcomes will reflect the joint role of ability and preferences.

### 2.4 Joint Effects of Ability and Preferences on Startup Job Choice

While the literature has largely considered ability and preferences separately or assumed homogeneous preferences, we consider heterogeneity in both ability and preferences jointly. Doing so allows for different combinations of ability and preferences that yield unique expectations regarding which individuals should choose to work in a startup versus an established firm. For simplicity, we consider four broad categories of workers, defined by different combinations of ability (high vs. low) and career preferences (founder/joiner vs. established firm types). Given that founder and joiner types share similar preferences for startup employment, we combine them into a single category of "startup types" to contrast them more clearly with established firm types (see Figure 1).

[8] Consistent with the prior literature on which we build, we conceptualize preferences as stable at least in the near term (i.e., between graduate school and individuals' first job search) (Halaby 2003, Stern 2004, Elfenbein et al. 2010). Although we expect that stated career preferences will significantly shape early-employment outcomes, we recognize that some individuals may initially choose other types of jobs for certain short-term benefits such as gaining industry knowledge or to discover entrepreneurial opportunities. As such, career preferences will not be perfect predictors of first-time job choices.

[9] For example, lower quality startups may offer less interesting or less cutting-edge technologies, or they may impose greater employment risks relative to more promising startups.

[10] Consistent with this idea, Bryan et al. (2022) show that information about startup quality influences workers' beliefs about a startup's potential success and the likelihood of workers applying to that startup.

If, as argued above, the productivity benefits are greater in established firms than in startups while the preference benefits are greater in a worker's preferred firm type, then ability and preferences are *reinforcing* for high ability established firm types who will maximize both productivity and preference benefits when working in established firms. Although low ability established firm types do not expect the same level of productivity benefits from working in an established firm as their high ability peers, ability and preferences are still reinforcing such that low ability established firm types should also seek employment in established firms rather than startups.

In contrast, ability and preferences are *offsetting* for startup types, who face a trade-off between the greater preference benefits of working in a startup and the opportunity costs of forgoing greater productivity and higher pay in an established firm. Assuming that the preference benefits of working in a startup are largely independent from ability, this trade-off is greatest for high ability startup types who face higher opportunity costs from not working in resource-rich established firms. Although we do not have priors on whether high ability startup types will consider the preference benefits to be greater than the opportunity costs, this discussion suggests that high ability startup types may be less likely to seek startup employment than low ability startup types. On the other hand, if the preference benefits

Considering ability and preferences jointly raises the question of whether they are correlated (see Jovanovic 1994). Our discussion in §2.2 suggests that if established firms offer greater financial returns to ability, then high ability individuals may prefer to work in an established firm. In that case, ability and established firm career preferences would be positively correlated and yield the same prediction, namely that high ability individuals will work in established firms. However, career preferences in our conceptualization reflect a much broader range of factors, including not only income but also non-pecuniary factors such as autonomy, risk, and intrinsic rewards from working on cutting-edge technologies, suggesting that ability and career preferences may not be correlated. Given that there is little theoretical rationale or prior evidence suggesting a strong relationship between ability and career preferences, we should see that some high ability individuals prefer to work in an established firm while others prefer to work in a startup. We will show in §4.1 that there is indeed no systematic relationship between ability and career preferences in the data, supporting our conceptual and empirical approach to considering them as independent factors.

### 2.5 Demand for Startup Human Capital

Up to this point our focus has been on workers' (supply-side) job choice. However, whether workers can choose their preferred job also depends on firms' demand for workers of differing ability. The implications for individuals with established firm preferences are quite clear. As argued in §2.1, established firms will seek to hire both high and low ability workers for different types of R&D projects, and thus most individuals, regardless of ability, should have job options in established firms. Given that high ability established firm types expect greater productivity benefits from working in an established firm, they should be the least likely to work in a startup followed by low ability established firm types.

The implications of demand are more ambiguous for startup types. We argued that early-stage technology startups seek to hire high ability workers to commercialize cutting-edge technologies.[11] As such, high ability startup types should be more likely than low ability startup types to receive startup job offers, and thus have the option to act on their preferences to work in a startup. At the same time, they face greater opportunity costs in forgoing established firm employment. If they find the preference benefits of startup employment greater than the opportunity costs, then they should be more likely to accept a startup job offer. Moreover, if the number of startup jobs is small relative to the number of applicants, then startups can "cherry pick" the most talented workers, leaving low ability startup types to take more readily available jobs in established firms. In that case, the share of high ability workers would be higher in startups than in established firms. If, on the other hand, high ability startup types consider the opportunity costs of working in a startup too high, then startups must "settle" for low ability startup types who are more likely to accept given their preferences and lower opportunity costs.

Figure 1 summarizes our conceptual framework and predictions for the four ability-preference combinations in terms of transitions into startup employment. Some of the predictions are unambiguous and testable. However, the actual shares of individuals in each cell as well as the trade-offs between benefits and opportunity costs – as reflected especially in the job choices of high ability startup types – require empirical exploration.

## 3 Data and Measures

Examining the role of ability and preferences in employee job choice presents two key empirical challenges. First, ability and preferences are often unobservable. As such, many studies infer ability or preferences from observed wages (Brown and Medoff 1989, Ouimet and Zarutskie 2014, Sorenson et al. 2021), or account for them through fixed effects (Abowd et al. 1999, Stern 2004, Kim 2018, Sorkin 2018, Bhaskarabhatla et al. 2021). While such approaches can be extremely useful, they typically do not allow researchers to estimate the separate roles of both ability and preferences on employment outcomes. Second, most data sources observe workers after they have made their first employment choice, making it difficult to distinguish selection into different types of firms from the potential treatment effects of the employment context on workers' ability or preferences (Sørensen 2007, Elfenbein et al. 2010). For

[11] We assume that firms will hire primarily for ability and that workers' preferences, which are typically unobservable to prospective employers, play little role in hiring decisions.

example, when observing employees' preferences after they are employed in a startup it is difficult to discern whether these preferences determined individuals' decision to work in a startup or whether startup employment itself influenced their preferences.

We overcome these challenges through a longitudinal survey that includes direct measures of both individuals' ability and stated preferences *prior* to entry into the job market.[12] This novel research design allows us to examine the separate roles of ability and preferences in explaining first-time employment outcomes. We also draw upon survey responses on startup job applications and job offers, starting compensation, and ex post job attributes and reasons for job choice to examine underlying assumptions of our conceptual framework and to explore alternative explanations. Although our data have their own limitations, they allow us to provide valuable insights on workers' sorting into different types of firms.

### 3.1 Survey strategy and supplementary data

Our survey follows a cohort of science and engineering PhDs from 39 top-tier U.S. research universities from graduate school to their first industry employment. We selected universities based primarily on PhD program size while also ensuring variation in private/public status and geographic region. The 39 universities in our sample produced roughly 40% of the graduating PhDs in science and engineering fields in 2009 (National Science Foundation 2009). Respondents were contacted through their university email address listed on department websites and invited to participate in an online survey that asked about their graduate school experience and career goals, using up to three reminders. Respondents were first surveyed in 2010 or 2013 while in graduate school (*PhD survey*, 10,781 respondents, 30% response rate adjusted for undelivered emails) and then again after graduation in 2013 and 2016 after they had transitioned into full-time employment (*employment survey*, 73% adjusted response rate). Together, the *PhD* and *employment surveys* provide detailed micro data on individuals' stated preferences and characteristics up to 3 years prior to their first industry employment, as well as information on their job search and first full-time job, including starting pay and employer characteristics.

To ensure comprehensive data on employment outcomes, we supplemented the *employment survey* with career profile data from LinkedIn and a Google search for all respondents to the *PhD survey*. We first searched for each respondent by name and PhD university, and then verified the match by comparing the field of study and the specific years in the PhD program as reported in the *PhD survey*. These external career profile data provide employment outcomes for non-respondents to the *employment survey*, as well

[12] This survey was approved by the Georgia Tech IRB, Protocol #09152 and Cornell University IRB, # 1707007286A003.

as more detailed data on job title and employer characteristics for all respondents. Combining survey and external data provides employment outcomes for 92% of *PhD survey* respondents.

Our sample consists of 2,394 PhDs who entered U.S. industry employment in R&D-related occupations between 2010-2016 and for whom we have complete data from the *PhD survey*. We restrict the sample to R&D-related occupations to focus on workers choosing between similar jobs in startups and established firms, as well as because these are the most prevalent first industry occupations for science and engineering PhDs (82.5% of industry-employed respondents in our data).[13] R&D-related occupations are identified based on either survey-reported work activities (i.e., respondents who reported that they spend 40-100% of their time on basic research, applied research, and/or development work activities) or the LinkedIn job title (e.g., research scientists, research engineer, data scientist, etc.). For PhDs where we have both survey-reported work activities and LinkedIn job titles, the correspondence for R&D occupations is 95.8%. While studies employing administrative data such as the U.S. Census or Statistics Denmark typically rely upon indirect proxies of founder status such as being among the first or highest paid employees (Sørensen 2007, Azoulay et al. 2020), we are able to directly identify founders and startup executives (e.g., CTO) and exclude them from our sample of employees.[14]

Despite our focus on recent doctorates taking jobs in different types of firms, it is useful to understand whether and how PhDs who go into industry differ from those who remain in academia. Table A1 in the *Appendix* uses the full survey data to compare our sample of industry PhDs to PhDs who remained in academia either as a postdoc or in a tenure or non-tenure track university position with respect to ability and preferences as measured prior to graduation in the *PhD survey*.[15] The results show no significant differences in ability. However, PhDs who transitioned to industry reported stronger preferences for financial pay and commercialization activities, as well as weaker preferences for autonomy and basic research activities (see also Roach and Sauermann 2010, Agarwal and Ohyama 2013). For our purposes, two points are particularly important. First, PhDs entering industry are less "academic" than those who remain in academia, stating quite balanced preferences for both non-pecuniary factors such as autonomy as well as financial compensation (see summary statistics in Table 1). As such, the trade-offs between pecuniary and non-pecuniary job attributes discussed in §2.4 should be of high relevance. Second, despite

[13] Although our discussion highlights differences between startups and established firms, we assume that they compete with each other in the same PhD labor market. Information on overlapping job applications and offers support this assumption (§4.4). This labor market is quite competitive, as evidenced by extremely low unemployment and earnings that are well above national population averages (National Science Board 2014).
[14] To examine the representativeness of our sample, we benchmarked it to data from the Survey of Doctorate Recipients, a biennial survey of science and engineering PhDs in the U.S. workforce conducted by the U.S. National Science Foundation. Our sample is comparable to the SDR in terms of the share of recent doctorates employed in industrial R&D as well as the share of PhDs across fields of science and engineering (details available from the authors).
[15] In our sample of industry PhDs, 77% went directly to industry after graduation and 23% first did a postdoc.

self-selection into industry, there remains significant heterogeneity within our sample with respect to both ability and preferences, allowing us to investigate potential sorting into startups versus established firms.

## 3.2 Variables

### 3.2.1 *Employment in Early-Stage Startups*

To identify whether an individual's first industry job was in an early-stage startup, we rely upon both the *employment survey* and LinkedIn data in a two-step process. First, we asked respondents in the *employment survey* to state their first employer's age (years since founding) and size (number of employees) at the time they started employment.[16] For individuals who did not respond to the *employment survey* or for whom firm age and size were missing, we used LinkedIn data to ascertain employer age and size in the year they started their job.

Much of the prior research examining startup human capital has focused on either firm size or age separately, typically using continuous measures of these firm attributes (Brown and Medoff 2003, Gompers et al. 2005, Ouimet and Zarutskie 2014, Dahl and Klepper 2015). Our approach combines both size and age to distinguish early-stage startups as qualitatively different from other types of employers (see also Burton et al. 2018, Sauermann 2018, Sorenson et al. 2021). We code individuals as working in an early-stage startup if their employer was founded within 5 years and had 50 or fewer employees in the year they started employment. All other individuals were coded as working in an "established" firm, which includes large established firms (e.g., Google), as well as corporate spinoffs (e.g., Google Life Sciences spinoff Verily) and high-growth ventures (e.g., 23andMe, Uber, etc.) that are both young and large. We examine the robustness of our results to alternative operationalizations of startup employment and to the stage of startup VC funding in §4.6.

In our sample, 11.6% of PhDs are employed in early-stage startups. Among these, 45% are employed in startups with 10 or fewer employees and the average startup age is 2.7 years, illustrating that in our sample early-stage startups are indeed very small and young firms. The preponderance of our sample work in R&D-intensive firms in high-tech industries. Among startup employees, 35% are in computer and information technology, 28% in biotechnology or other biomedical, 15% in R&D services, and 3% in energy. Among established firm employees, 42% are in computer and information technology, 17% in

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[16] To measure firm age, we asked survey respondents whether their employer was founded within the past five years, 6-10 years, or greater than 10 years when they started employment. LinkedIn provides the firm founding year, which we subtracted from the first year of employment and coded to correspond to the survey measure. To measure firm size, respondents were asked to report the total number of employees using a range of categories, including 1-10 and 11-50 employees. LinkedIn also reported the number of employees using the same categories. We manually searched news articles and other sources for information to confirm the number of employees at the time of first employment for young firms with more than 50 employees.

biotechnology or other biomedical, 10% in R&D services, and 3% in energy. Leading technology firms such as Amazon, Dow Chemical, Genentech, Google, Intel, Microsoft, Pfizer, and Qualcomm account for a large share of established firm employment in our sample.

#### 3.2.2 *Ability*

Prior entrepreneurship research has used a variety of proxies for unobserved worker ability, including educational attainment, work experience, and prior wages (Hamilton 2000, Elfenbein et al. 2010, Åstebro et al. 2011, Agarwal and Ohyama 2013, Ouimet and Zarutskie 2014), while others have accounted for ability through individual fixed effects (Abowd et al. 1999, Stern 2004, Kim 2018, Babina et al. 2019). Given that our sample consists of PhDs at the beginning of their careers, commonly used proxies either do not vary (e.g., level of education) or are unavailable (e.g., prior wages). Instead, we follow recent work by employing a fine-grained measure of ability that is particularly relevant when considering PhD employment outcomes and performance: the quality of PhD students' university department (Agarwal and Ohyama 2013, Roach and Sauermann 2015, Cohen et al. 2020).[17] Department rank is a useful proxy for PhD ability given that highly ranked departments are more selective in admitting PhD students and provide more rigorous scientific training. In addition, PhDs from higher ranked departments likely expect to be more productive in their R&D activities and to have better employment prospects than PhDs from lower ranked departments. Moreover, in our context PhD department ranking is an observable signal to employers of a worker's potential ability and should be particularly important for novice employees that lack industry work experience (Spence 1973, Agarwal and Ohyama 2013, Hegde and Tumlinson 2021). Finally, in contrast to wages, which may reflect ability as well as compensating differentials, our measure is distinct from employment outcomes and thus is well-suited to juxtapose to career preferences when examining startup employment.

To construct our ability measure, we matched respondents' university departments to the National Research Council's (NRC) rankings of doctoral programs, which reflect aspects such as research funding and faculty publication productivity (National Research Council 2010).[18] To facilitate interpretation, we reverse-coded PhD department rank so that positive regression coefficients indicate a positive relationship between ability and the outcome variable. Given the skewed distribution of this measure, we use the natural log in regression analyses, as well as categorical variables for ability quartiles.[19]

[17] Although we interpret PhD department rank as a proxy for ability, it may also reflect other factors such as university status.
[18] PhD department rankings are not available for some university departments. In such cases, we used the broad field average (e.g., the average of all engineering departments when a specific engineering department ranking is missing).
[19] Results are substantively identical when using the raw measure.

To examine the validity of PhD department rank as a proxy for ability, we regress starting earnings as reported in the *employment survey* onto PhD department rank while controlling for demographics, degree field, and year of employment. The intuition is that if employers use department quality as a signal of PhDs' ability, then department rank should significantly predict starting pay above and beyond other observable characteristics. The results reported in the *Appendix* (Table A2) confirm this intuition, supporting our interpretation of PhD department rank as a meaningful proxy for ability.

In our sample, PhD department rank reflects 677 different university departments across a broad range of fields. As such, this measure is much more fine-grained and closer to the individual level than commonly used coarse ability measures such as highest degree (e.g., high school, bachelor's, master's) or years of education (for notable examples see Card 1996, Abowd et al. 1999, Hamilton 2000). At the same time, PhD department rank does not vary across individuals within a department. To examine the robustness of our results to this potential limitation, we constructed an alternative individual-level ability measure using a regression approach that incorporates information from signals of individual ability including publications, patents, research awards, and starting pay (see *Appendix B* for details). Although this approach has its own limitations, it yields substantively identical results as using PhD department rank, strengthening confidence in our ability results.

### 3.2.3 *Preferences*

As discussed in §2.3, ex-ante preferences can be conceptualized with respect to careers in a startup or established firm, as well as to specific job attributes such as autonomy and risk. Although our focus is on the former, we also measure certain job attribute preferences that are particularly relevant for startup employment and that help us understand our career preference measures.

**Preferences for specific job attributes.** We measure preferences for five job attributes that may distinguish individuals drawn to employment in a startup or an established firm (see §2.3). First, we proxy for risk tolerance using a lottery-type question that asked respondents: "Imagine you have the choice between winning $1,000 for sure or winning $2,000 with a 50% chance. Please indicate which option you prefer." Respondents answered using a 10-point scale that ranged from "strongly prefer a 100% chance to win $1,000" to "strongly prefer a 50% chance to win $2,000." Higher values reflect a greater willingness to choose a riskier outcome with a higher potential payoff, which we interpret as a greater tolerance for risk. Second, we build on the Survey of Doctorate Recipients (National Science Foundation 2008) to measure respondents' preferences for autonomy ("freedom to choose research projects") and income ("financial income") by asking them to rate the importance of these job attributes on a 5-point scale ranging from "not at all important" (1) to "extremely important" (5). Finally, we measure individuals' preferences for managerial work activities ("management or administration") and commercialization work activities ("commercializing research results into products and services") on a 5-point scale ranging from "extremely uninteresting" (1) to "extremely interesting" (5).

**Career preferences.** We measure ex ante career preferences using a question in the *PhD survey* that asked respondents "Putting job availability aside, how attractive or unattractive do you personally find each of the following careers?", where careers included "startup job with an emphasis on research or development" and "established firm job with an emphasis on research or development", as well as other careers not used in this study, such as university faculty. Respondents rated each career independently using a 5-point scale ranging from "extremely unattractive" (1) to "extremely attractive" (5). By explicitly asking respondents to disregard current labor market conditions, we seek to capture PhD students' career preferences independent of exogenous factors that may affect career outcomes, such as perceived job availability (Stephan 2012, Roach and Sauermann 2015). We also captured respondents' founder intentions by asking in a separate question "How likely are you to start your own company?", using a 5-point scale ranging from "definitely will not" (1) to "definitely will" (5).

Given that ratings of career attractiveness are not mutually exclusive, we employ a three-step process to construct relative measures of career preferences. First, we code as *founder types* respondents who reported an intention of starting their own company (i.e., "likely will" or "definitely will") and whose founder intention was equal to or greater than their attractiveness of working in an established firm.[20] Second, we code the remaining individuals who rated the attractiveness of working in a startup as greater than that of working in an established firm as *joiner types,* and individuals who rated working in an established firm as more attractive than working in a startup as *established firm types.* This approach codes as *joiner types* individuals who prefer to work in a startup but who do not have founder intentions. Respondents who reported that working in a startup and an established firm were equally attractive (e.g., both "extremely attractive") are coded as *indifferent types* and are used as the comparison group in our regression analyses.[21] The remaining individuals are not attracted to working in either a startup or an established firm and are coded as *other types*.[22] In our sample, 4.1% of respondents are founder types, 7.6% are joiner types, 41.7% are indifferent types, 36.5% are established firm types, and 10.1% are other types. An advantage of these broader career preference measures over preferences for specific job attributes is that they likely reflect preferences for a more comprehensive "bundle" of job attributes

[20] Among founder types, 89% also reported that a startup career was either "extremely attractive" or "attractive" compared to 63% who reported that an established firm career was either "extremely attractive" or "attractive".
[21] Our approach of coding preferences as relative differs from that used by Roach & Sauermann (2015) who classified all respondents who were attracted to working in a startup and did not have founder intentions as joiners, regardless of their interest in other careers such as established firms.
[22] In our sample of PhDs, *other types* are primarily attracted to university faculty careers.

offered by different types of firms, as well as other unobserved factors such as social influences (Stuart and Ding 2006, Sørensen 2007, Azoulay et al. 2017) or occupational identity (Akerlof and Kranton 2000).

To provide insights into our career preference measures, we regress stated career preferences onto preferences for specific job attributes discussed above as well as other relevant variables. To provide a more general comparison between individuals who want to work in a startup versus an established firm, we combine founder and joiner types into a single category of "startup types". The results in Table 2 show that startup types exhibit significantly stronger preferences for autonomy and commercialization work activities, and significantly weaker preferences for financial pay than established firm types. We find no difference in ability or risk tolerance. Consistent with our discussion in §2.3, these results indicate that startup types exhibit stronger preferences for non-pecuniary job attributes associated with startup employment and weaker preferences for financial compensation than established firm types (see also Roach and Sauermann 2015). Career preferences may also be shaped by the university context in which PhDs were trained (Stuart and Ding 2006, Azoulay et al. 2017). Indeed, startup types are more likely to come from university labs that encouraged careers in startups and where the advisor had founded a company (as reported in the *PhD survey*), and less likely to come from labs that encouraged careers in established firms. Men and foreign-born PhDs are also more likely to be startup types.

Despite the strong association between preferences for startup careers and specific job attributes, one might be concerned that PhD students have limited information about industry jobs and may not see a clear distinction between working in startups or established firms. Using measures of ex ante expectations of the availability of job attributes from the *PhD survey*, we show in the *Appendix* (Table A4) that students expect significant differences between startups and established firms with respect to pay, R&D resources, job security, autonomy, and intellectual challenge. These differences are tightly aligned with our characterization of startups and established firms in §2.1. While we do not claim that graduate students have perfect information, these results confirm that they have reasonable expectations of differences between jobs in startups and established firms when stating their career preferences.

#### 3.2.4 *Control Variables*

We control for several *demographic characteristics*, including gender, marital status, children, and whether respondents did postdoctoral training prior to industry employment. Given that job choices of international students may be constrained by their need to secure a work visa after graduation (Roach and Skrentny 2019), we also use survey responses to distinguish graduates who are U.S. citizens or permanent residents from foreign PhDs who require a work visa for industry employment in the U.S. We use PhD *degree field fixed effects* for 14 detailed fields within the broader fields of life sciences, chemistry, physics, engineering, and computer science.

Finally, employment outcomes depend not only on individuals' choices, but also on *labor market conditions* (see §2.5). To control for the general demand for human capital in startups, we include the annual amount of VC funding for early-stage ventures (angel, seed or Series A) in the year that an individual started employment. Our rationale is that technology startups use a large share of their funding to hire human capital such that the availability of VC funding should be positively correlated with startup job availability. We control for macroeconomic factors that may improve general private sector job availability by including the annual U.S. GDP growth rate.[23] We explore the role of firm demand more directly in additional analyses using data on job offers, as described below. Other measures used to explore mechanisms and to probe the robustness of our results are also discussed below.

### 3.2.5 *Survey Measurement Issues*

There are general concerns when using survey data. One is common methods bias, which occurs when dependent and independent variables are measured using the same method (e.g., survey rating scales) and may result in inflated correlations between variables (Podsakoff et al. 2003). This is not a concern for our study since our dependent and independent variables are measured using different scales or data sources such as LinkedIn. A second concern with self-reported survey measures is that respondents may overstate preferences that seem socially desirable, especially in the eyes of peers or advisors. We partly addressed this concern by assuring respondents in the survey invitation that all responses would be kept strictly confidential. While any remaining social desirability bias may affect descriptive statistics (e.g., shares of founder or joiner types), it would affect regression analyses only to the extent that it is associated with unobserved respondent characteristics that are correlated with other featured variables. Our rich set of control variables should capture much of this typically unobserved heterogeneity.

## 4 Results

We first present key descriptive patterns (§4.1), followed by our main analyses examining the roles of ability and preferences in predicting startup employment, both separately (§4.2) and jointly (§4.3). Next, we investigate the role of startup demand using more detailed data on startup job applications and job offers (§4.4). We then provide supplemental analyses that relate our findings to the literature on startup earnings and compensating differentials, as well as provide additional evidence on ex post job attributes and workers' reasons to take startup jobs (§4.5). Finally, we discuss the robustness of our results (§4.6).

[23] VC data come from PricewaterhouseCoopers MoneyTree (https://www.pwc.com/us/en/technology/moneytree/explorer.html) and GDP data from the Bureau of Economic Analysis (https://www.bea.gov/iTable/index_nipa.cfm). We also estimated models that included job year fixed effects instead of annual VC funding and GDP growth rate with substantively identical results.

### 4.1 Descriptive Results

Table 1 reports summary statistics for the full sample, as well as by employment type and career preferences. Across the full sample, 11.6% of workers are employed in startups. The average ability of startup employees as measured by PhD department rank is higher than the average ability of established firm employees (-13.36 vs. -16.80, smaller absolute values indicate higher rank). Panel A of Figure 2 plots the share of startup employees for each quartile of the ability distribution, showing that the share of startup employees in the highest ability quartile (17.8%) is roughly twice as large as the share in the lowest ability quartile (8.7%). These patterns illustrate that ability has a positive relationship with startup employment in our sample of science and engineering PhDs. With respect to career preferences, Panel B of Figure 2 shows that a higher share of founder (26.7%) and joiner (23.5%) types work in a startup, compared to a much lower share of established firm types (7.5%). These patterns indicate a strong relationship between career preferences and employment outcomes.

As per §2.4, our conceptual model of ability and preferences as two distinct dimensions is most relevant if ability and career preferences are not strongly correlated. Confirming that this condition is met, Table 1 shows that there is no significant difference in PhD department rank between joiner and established firm types (t-statistic = 1.124, p = 0.262) or founder and established firm types (t-statistic = -0.551, p = 0.582). A more detailed contingency table analysis also shows no significant association between ability quartiles and career preferences (*Appendix* Table A5).

### 4.2 Ability and Preferences as Predictors of Startup Employment

We now examine whether ability and ex ante preferences predict ex post startup employment using regression analysis. Following our conceptual framework, we first examine the effects of ability and preferences separately. Table 3 presents logistic regressions predicting whether graduates' first industry job is in an early-stage startup (coded as 1) or an established firm (coded as 0).[24] Robust standard errors clustered on university are reported in parentheses.

As discussed in §2.2, ability sorting theories focusing on productivity and income predict that high ability workers will be less likely to work in resource-constrained startups. Contrary to this prediction, Columns 1-4 show that higher ability employees (i.e., PhDs from higher ranked university departments) are more likely to work in a startup. Estimates from Model 3, our preferred specification, indicate that a

[24] Analyses using linear probability models yield the same results (see *Appendix* Table C1).

one standard deviation increase in PhD department rank is associated with a 32% higher likelihood of startup employment.[25]

Model 1 also includes preferences for specific job attributes. Individuals who are more risk tolerant, have a stronger preference for autonomy, and express a greater interest in commercialization work activities are more likely to work in a startup, while individuals with a stronger preference for managerial work activities are less likely to work in a startup.[26] A preference for financial pay has a negative but insignificant relationship with startup employment. Model 2 includes career preferences with preferences for specific job attributes. Compared to individuals who are indifferent between working in a startup or an established firm (omitted category) founder and joiner types are significantly more likely to work in a startup, while established firm types are significantly less likely. The reduced significance of preferences for autonomy and commercialization suggests that they are mediated through career preferences (see §2.3), while risk tolerance is partially mediated. The strong main effects of career preferences indicate that they are important in their own right and likely capture other factors such as preferences for other job attributes not included in our model, social influences, and individuals' career identity (see §3.2.3).

Model 3 excludes job attribute preferences to focus on the career preferences highlighted in our conceptual discussion. Using this regression as our preferred model, we find that founder types are nearly three times as likely (odds ratio of 2.942) and joiner types nearly twice as likely (odds ratio of 1.915) to work in a startup as indifferent types, while established firm types are about half as likely (odds ratio of 0.576).[27] The estimates of ability are not sensitive to the inclusion of career preferences, indicating that ability and career preferences are not correlated. The results for ability and career preferences are robust to controlling for the nature of R&D activities and other ex post job attributes (*Appendix C, Table C2*).[28]

An important concern with measuring ability using PhD department rank is that it may reflect aspects of the entrepreneurial context of the department, university, and/or region rather than ability. For example, PhDs from MIT and Stanford are not only higher ability but are also located in entrepreneurial universities and regions that may foster startup employment. To account for this, Model 4 controls for whether they did their PhD in an entrepreneurial region (i.e., Boston and San Francisco), as well as survey

[25] Regressions using ability quartiles show that workers in the highest quartile are more than twice as likely to work in a startup compared to workers in the lowest quartile (odds ratio of 2.09, $p < 0.001$), consistent with the patterns observed in Fig. 2a.
[26] A one standard deviation increase in the independent variable increases the likelihood of working in a startup by 15.0% for risk tolerance, 13.8% for a preference for autonomy, and 11.6% for a preference for engaging in commercialization activities.
[27] Compared to established firm types, founder types are five times as likely (odds ratio of 5.105) and joiner types are over three times as likely (odds ratio of 3.324) to work in a startup.
[28] We find no significant differences in employment outcomes by gender, marital status, or the number of children in our sample. Foreign workers requiring visa sponsorship are less likely to work in a startup (see also Roach and Skrentny 2019). One might be concerned that lower ranked departments have a higher share of international PhDs, thereby introducing a correlation between ability and visa requirements. Our results are robust to a model that excludes international students from the sample.

responses on whether their advisor founded a startup and whether lab norms encouraged startup employment. As expected, PhDs from universities in entrepreneurial regions are more likely to work in a startup. However, even after controlling for these factors, PhD department rank remains positive and highly significant, suggesting that our results are not driven by university or region effects.[29]

As discussed in §3.2.2, an additional concern with the PhD department rank measure is that it does not vary across individuals within a department. To account for this, we constructed an alternative individual-level ability measure through a regression approach that uses observable signals of ability including publications, patents, research awards, and starting pay (see *Appendix B* for details). Model 5 shows that this *ability index* also significantly predicts startup employment. The coefficients of career preferences are largely unchanged, indicating that our key results on both ability and preferences are robust to using two different proxies for ability. We report additional robustness checks in §4.6.

### 4.3 The Joint Role of Ability and Preferences

Building on our conceptual discussion (summarized in Figure 1), we now examine the joint roles of ability and career preferences. To compare different combinations of ability and preferences (e.g., high ability joiner types, low ability established firm types, etc.), we first use ability quartiles to construct categorical variables for "high" (76-100%) and "low" (0-25%) ability workers and combine the two middle quartiles into an "average ability" category. To simplify the analysis of career preferences, we combine founder and joiner types into "startup types". We then construct categorical variables for each combination of ability and career preferences. This approach results in twelve categorical variables that reflect all possible combinations of ability (high, average, and low) and career preferences (startup, indifferent, established firm, and other types). Regressions using these categorical variables estimate the combined effects of ability and preferences, including potential reinforcing and offsetting effects (see §2.4).[30] Table 4 summarizes results from logistic regressions that compare startup employment outcomes between our four featured ability-preference combinations; each column reports the comparison as odds ratios relative to a different omitted combination to facilitate the interpretation (the underlying logistic regressions are available from the authors).

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[29] The entrepreneurial context variables may over-control by capturing variation across departments that should legitimately be reflected in our measure of ability. For example, fixed effects for Boston and San Francisco control for not only entrepreneurial context but also for the objectively higher ability of graduates in our sample from Harvard, MIT, Stanford and Berkeley. For this reason, we include these variables as a robustness check rather than as controls in all our models.

[30] Note that the coefficients of these variables should not be interpreted as traditional "interactions". Our set of combination variables captures mutually exclusive groups and the regressions do not include separate main effects of ability and preferences.

First, we predicted in §2.4 that high ability established firm types should be least likely to work in a startup due to the reinforcing productivity and preference benefits from established firm employment. Although high ability established firm types (Column 2) are less likely to work in a startup than both high and low ability startup types (0.280 and 0.583 lower odds, respectively), they are *more likely* to work in a startup than low ability established firm types (1.920 greater odds). This is consistent with the earlier finding of a positive coefficient of ability in Table 3, which we explore in more detail below.

Next, the predictions regarding high ability startup types were ambiguous because these individuals face a stronger trade-off between the preference benefits from working in a startup and the higher opportunity costs of forgoing greater productivity and pay in an established firm. Column 1 suggests that the benefits outweigh the costs: High ability startup types are significantly more likely to work in a startup than all other ability-preference combinations. Importantly, the finding that even among startup types, high ability are more likely to work in a startup cannot be explained by supply-side considerations alone. Building on our discussion in §2.5, we will explore the role of startup demand for high ability workers as a potential explanation below. Finally, low ability startup types (Column 3) are more likely to work in a startup than both high and low ability established firm types (1.715 and 3.293 greater odds, respectively), likely reflecting their higher expected preference benefits from startup employment.

Figure 3 presents the predicted likelihoods of working in a startup for each ability-preference combination, visualizing how the joint effects of ability and preferences add up to considerable differences in employment outcomes. For example, the likelihood of high ability startup types working in a startup is 29.6%, while the likelihood of low ability established firm types is 6.2%.

### 4.4 Startup Job Applications and Job Offers

Our main results show that ability and preferences in combination are important in explaining who works in a startup. However, our conceptual framework implies that preferences and ability should play different roles at different stages of the job market process, reflecting two different kinds of selection: individuals should self-select into applying to startup jobs based primarily on preferences (§2.3), while startups should select applicants based primarily on ability when making job offers (§2.5).

To gain deeper insights into the distinct roles of ability and preferences in the job market process, we utilize a question that asked respondents in the *employment survey* “When you were searching for your first industry job, did you apply for and/or receive job offers from startups or established companies?” Respondents answered yes or no separately for “applied for at least one startup job” and “received at least one startup job offer.” Among the 1,371 PhDs who responded to this question, 66% of founder types and 58% of joiner types applied to at least one startup job, compared to 47% of indifferent types and 40% of established firm types.[31] For comparison, 96.5% of respondents reported applying to at least one established firm job and 95.0% of these received at least one offer with only minor differences by career preferences. These patterns confirm that established firms are the default employment option.

In the first stage, workers choose whether to apply to startup jobs, which we examine using startup job applications from the survey as the dependent variable (Table 5, Column 1). Ability-based theories of job choice predict that high ability workers will be less likely to apply to startup jobs given expectations of lower productivity and income (§2.2), while preference-based theories predict that founder and joiner types will be more likely to apply to startup jobs (§2.3). Although the coefficient of ability is negative, it is not statistically significant. As expected, founder and joiner types are significantly more likely to apply to startups than indifferent types, while established firm types are less likely to apply. The finding that ability does not significantly predict startup job applications may indicate that preferences matter more when applying to startup jobs, or that startups may be attractive to many high ability workers, perhaps due to opportunities to work on cutting-edge technologies. We explore this possibility in §4.5.

In the second stage, startups select among applicants to make job offers. Consistent with our expectation (§2.5), Column 2 shows that conditional upon applying, higher ability workers are more likely to receive a startup job offer (i.e., startups make offers to PhDs from higher ranked departments). Although founder types are more likely to receive a startup job offer, we do not find a difference across other types, suggesting that startups make offers primarily based on ability and not preferences. Even though startups are dependent on recruiting high ability workers to commercialize cutting-edge technologies, making offers based on ability is not unique to startups since high ability workers should be more productive in all types of firms. As such, the more interesting insight emerges when considering the results of Columns 1 and 2 in conjunction: Given that graduates apply to startups primarily based on career preferences rather than ability, the applicant pool includes enough high ability individuals such that startups are able to "cherry pick" talented workers despite offering lower complementary assets and pay.

In the final stage, individuals who received a startup job offer choose whether to accept, leading to the observed employment outcomes. Column 3 shows that conditional upon receiving a startup job offer, high ability workers are more likely to work in a startup. Again, this result is contrary to the prevailing view that high ability workers will choose jobs in established firms over startups (§2.2). As expected, the decision to accept a startup job offer is also explained by career preferences, with founder and joiner types significantly more likely to work in a startup, while established firm types are less likely.

[31] Data on job search are only available for individuals who responded to the *employment survey*. We replicated our main analyses in Table 3 using this smaller sample with identical results, alleviating concerns of potential non-response bias.

Although our interpretation of Column 3 implicitly assumes that workers choose between offers from startups and established firms, some workers did not apply to established firms or did not receive established firm job offers. Column 4 drops these cases to focus on workers with offers from both startups and established firms. The results confirm that high ability workers are more likely to work in a startup even when they have offers from established firms. Although the coefficients of founder and joiner types are not statistically significant compared to indifferent types, joiner types are significantly more likely to work in a startup compared to established firm types (not shown). The weaker coefficients of startup career preferences may be due in part to a more homogeneous subsample of workers who applied to both startup and established firm jobs, excluding startup types who chose not to apply to established firms as well as established firm types who chose not to apply to startups (see Column 1).

### 4.5 Evidence on earnings, ex post job attributes, and reasons for job choice

The results presented thus far show that high ability PhDs are more likely to work in early-stage technology startups, and the strong preference-based self-selection suggests that many do so for non-pecuniary benefits. In the following, we provide additional evidence on the assumptions of our conceptual discussion (§2) and explore potential mechanisms underlying the main results.

#### *4.5.1 Earnings of startup and established firm employees*

A key assumption of our conceptual discussion was that startups have lower resources and pay lower salaries, creating a potential trade-off for high ability startup types who should expect greater preference-based benefits in startups, but greater productivity and financial returns in established firms (§2.4). Although our findings suggest that the preference benefits outweigh the opportunity costs for many high ability startup types (consistent with Stern 2004), an alternative explanation is that high ability scientists and engineers may be paid more in startups to compensate for startups' lower complementary assets (Bhaskarabhatla et al. 2021). To consider these alternative explanations, and to verify a key assumption of our model, we now compare the earnings of startup and established firm employees.

In the *employment survey* we asked respondents*:* "What was your total starting annual compensation (in US dollars), including base salary, annual bonuses, etc.?" Respondents reported their starting compensation on a sliding scale ranging from \$0 to \$300k. We also asked respondents whether they received equity or stock options from their employer (Y/N) as a control for this potential compensation mechanism. In our sample, 74.8% of startup employees and 41.3% of established firm employees reported receiving company stock options. Even though the share of startup employees receiving stock options is higher, we note that startup equity is very risky and does not have monetary value unless the venture has a successful liquidity event, while publicly traded established firms' stock options are tied to the current share price and thus have a known monetary value.

Table 6 reports OLS regressions with (log) starting earnings as the dependent variable. Column 1 estimates the difference in earnings between startup and established firm employees controlling for only demographic characteristics and degree field fixed effects. Startup employees earn 16% less than established firm employees. This supports the underlying premise of our conceptual discussion and is also consistent with prior results using administrative data (Haltiwanger et al. 2013, Ouimet and Zarutskie 2014, Burton et al. 2018, Sorenson et al. 2021). Column 2 includes measures of ability and career preferences, which are typically unavailable in administrative data. As expected, higher ability individuals earn significantly more: a one-SD increase in PhD department ranking is associated with 5.6% higher earnings. The estimated earnings gap between startup and established firm employees remains remarkably stable, with the former earning 17% less than their peers in established firms. Career preferences have no significant relationship with earnings. These results are robust to a model controlling for job attributes in *Appendix C* (Table C2). Although much of the prior literature has interpreted lower earnings in startups as evidence of lower startup human capital, our earlier finding that high ability employees are more likely to work in a startup suggests that the pay difference instead reflects a taste-based compensating differential.

Columns 3 and 4 estimate regressions for the split samples of startup and established firm employees to examine whether the roles of ability and preferences differ between employer types. Ability continues to predict higher earnings in established firms (Column 3) while the relationship is notably weaker and insignificant in startups (Column 4). To illustrate, the predicted starting salary of established firm employees in the highest ability quartile is $116,724 compared to $98,357 for employees in the lowest ability quartile. A stronger relationship between ability and earnings in established firms is consistent with the assumption that large firms possess greater resources to compensate high ability workers for their greater productivity (see §2.2). Early-stage startups, on the other hand, are resource constrained and thus unable to offer high ability workers extra pay to compensate for their higher productivity (which will only generate financial returns in the future if the venture is successful). While early-stage startup employees might also be compensated through equity, the results show that startup employees who receive equity do not earn less than startup employees who do not, suggesting that the role of equity may be more nuanced than simply to compensate startup employees for lower earnings.

Although one might expect that established firm types require higher pay in startup employment to compensate for the misalignment with their career preferences, the lack of significant coefficients for career preferences in Column 4 suggests that this is not the case. Our interpretation is that startups' resource constraints limit their ability to offer higher pay, and thus established firm types who find startup pay too low will instead work for higher pay in established firms. This, in turn, suggests that the small share of established firm types who work in startups despite receiving lower pay may do so because they expect additional non-pecuniary benefits in startup employment. We explore this possibility using additional survey questions in §4.5.3.

Perhaps more importantly, the result that high ability workers earn more in established firms but not in startups suggests that they take a greater wage discount to work in startups than low ability workers. This is consistent with our premise that the opportunity costs of startup employment are greater for high ability workers (§2.4). To verify this, we estimated earnings by ability quartiles for startup and established firm employees, including a broad set of controls (regression results available from the authors). Consistent with our premise, Fig. 4 shows startup employees in the highest ability quartile earn approximately $24,076 (20.6%) less than their peers in established firms, while startup employees in the lowest ability quartile earn $12,465 (12.7%) less than their peers in established firms.

Although these results suggest that high ability workers pay a large financial price for the non-pecuniary benefits of working in their preferred startup jobs, this does not rule out that they may also take startup jobs in expectation of greater financial compensation in the future. For example, individuals may expect that startup employment enables them to develop their human capital faster than employment in established firms, potentially leading to higher future pay (Campbell 2013). They may also expect that as the startup grows and secures funding they will be promoted and see their earnings rise more rapidly than they would in an established firm (see Sorenson et al. 2021). If such mechanisms are important to workers' startup job choice, then we would expect startup employees who earn less at the beginning of their careers to catch up and eventually surpass the earnings of established firm employees.[32]

To examine earnings trajectories, we utilize additional data for the subsample of workers who have been employed at least five years and who responded to a subsequent wave of the *employment survey* (n=986).[33] Column 5 replaces starting pay with current pay as the dependent variable, while also controlling for the number of years in industry employment (5-9 years in our sample). We find that current earnings of workers whose first job was in a startup is 14.7% less than that of workers whose first job was in an established firm, indicating that even after at least five years of industry employment the pay gap remains large and significant. These results also suggest that the cumulative difference in earnings widens over time. While we cannot rule out that some individuals chose to work in a startup at least in part due to expectations of higher future earnings, the observed persistently lower earnings are

[32] We thank an anonymous referee for suggesting this analysis.
[33] We also include responses from the 2019 wave of the survey for this analysis.

more consistent with workers receiving non-pecuniary benefits from startup employment that compensate for lower pay (Hamilton 2000, Stern 2004).[34]

#### *4.5.2 Ex post job attributes in startups and established firms*

In §2.2 we contended that startups pay less due to resource constraints, which also hinder their ability to offer complementary assets that increase worker productivity. At the same time, we suggested that startups offer non-pecuniary job attributes such as autonomy and opportunities to work on cutting-edge R&D projects that may enable them to attract high ability workers despite offering lower pay (§2.3). We now verify the underlying assumptions of these arguments using questions from the *employment survey* that asked respondents about different ex post job attributes.

To examine whether startups are indeed more resource constrained, we asked respondents to rate "their current level of resources for your R&D activities" on a 4-point scale from "extremely insufficient" (1) to "more than sufficient" (4). Column 1 in Table 7 regresses this measure onto startup employment while also controlling for degree field and job year fixed effects. Startup employees have significantly lower resources than established firm employees, consistent with our conceptual premise.

Turning to non-pecuniary job attributes, we first examine whether startups offer employees greater autonomy in their work. We asked respondents how much influence they have over choosing which R&D projects to work on, ranging from "no influence" (1) to "complete influence" (5). Again, consistent with our conceptual discussion, Column 2 shows that startup employees have significantly more autonomy than established firm employees. Next, we asked respondents the extent to which they agreed that their R&D activities are "'cutting-edge' (i.e., advanced areas of science and/or technology)" and "highly intellectually challenging", each rated on a 5-point scale from "strongly disagree" (1) to "strongly agree" (5). Consistent with our premise, startup employees more strongly agree that their R&D is cutting-edge (Column 3) and highly intellectually challenging (Column 4) than established firm employees. Of course, startups are not the only place to work on cutting-edge technologies: a quarter of established firm employees also report that their R&D work is cutting-edge. However, this relatively low share is consistent with our premise that established firms have a more diverse portfolio of R&D projects.

#### *4.5.3 Stated reasons for job choice and for working in a startup*

We complement the evidence on earnings and ex post job attributes with evidence on individuals' ex post stated reasons for taking their current job. In particular, the *employment survey* asked workers to

[34] We note that this simple analysis focuses on the first employer type and does not account for more complicated mobility patterns such as workers moving from startups to established firms or vice versa.

select “very important reasons” for choosing their first job, offering a number of pecuniary and non-pecuniary job attributes. Regressions comparing these reasons between startup and established firm employees (Table 8) reinforce the patterns reported in prior sections, as well as our discussion of potential drivers of career preferences (§2.3): Startup employees are significantly less likely to state higher compensation and job security as very important reasons for choosing their job than established firm employees, and are significantly more likely to report opportunities to work on cutting-edge technologies as having been very important. Although not reported in the table (results are available from the authors), when restricting the sample to individuals who received job offers from both startups and established firms, we find that those who choose to work in established firms are over five times as likely to report that higher pay (odds ratio 5.49) and job security (odds ratio 5.75), respectively, were very important reasons for their job choice. These results suggest that these two attributes are key reasons why workers turn down startup job offers. Career advancement is mentioned frequently by both startup and established firm employees, with no significant difference between the two groups.

We also asked startup employees whether the “startup idea seemed very promising” was a very important reasons for choosing their job. Approximately 66% of respondents across career preference types indicated that it was. This reinforces that even though startup employees appear to be drawn to startup employment for a variety of reasons – including non-financial benefits associated with a startup setting in general – they do not ignore the quality of startups. Thus, perceived startup quality may have played a role in workers’ choice between different startup offers (Bryan et al. 2022).[35]

We also seek to understand whether reasons for joining startups in particular differ between career preference types. Recall from §2.3 that founder types might choose to work in a startup specifically to build their entrepreneurial skills and learn to be a founder (Gompers et al. 2005, Sørensen 2007, Elfenbein et al. 2010), while joiner types are likely drawn to startup employment for reasons other than becoming a founder. Our conceptual framework also suggests that both founder and joiner types should consider startup employment a particularly good “fit” with their career preference, while established firm types should not. Finally, and related to the prior analysis, we speculated that high ability established firm types might work in startups due to opportunities to work on cutting-edge technologies.

We explore these reasons using a question that asked startup employees to select important reasons for working in a startup, including “I wanted to learn about entrepreneurship to help me startup my own company one day,” “I thought working in a startup would be a better fit for me than other job options”,

[35] We note that this reason is not cited more frequently by high ability workers than others, providing no evidence that high ability workers are more likely to join startups because they are (or believe to be) better able to identify the most promising new ventures. We thank an anonymous reviewer for this idea.

and “I am interested in the specific technology or industry”. Among founder types 63.2% reported learning about entrepreneurship as an important reason to work in a startup, compared to only 35.1% of joiner types, 37.5% of indifferent types, and 20.4% of established firm types, providing direct evidence that many aspiring founders expect startup employment will provide a valuable learning experience. We also find that a higher share of founder (78.9%), joiner (73.0%), and indifferent (74.0%) types report that working in a startup was a better fit for them compared to established firm types (53.1%). The share of startup employees who reported a strong interest in the startup’s technology is relatively high across preference types (63.2% of founder types, 73.0% of joiner types, 73.0% of indifferent types, and 67.3% of established firm types), reinforcing again that opportunities to work on interesting R&D projects make early-stage startups attractive to scientists and engineers. The number of established firm types working in startups is small, but the fact that most of them indicate an interest in the startup’s particular technology suggests a potential explanation for why they joined a startup despite their ex ante preference to work in an established firm and despite lower earnings. We also note that across these reason indifferent types are indistinguishable from joiner types, implying that they more strongly preferred to work in a startup and that ex post the preponderance of startup employees are “startup types”.

Although self-reported earnings, job attributes, and reasons for job choice should be interpreted with caution, the patterns reported in this section are largely consistent with our conceptual discussion as well as our interpretation of the main results. First, data on earnings expectations, starting earnings, earnings trajectories, and stated reasons for job choice suggest that financial returns do not play a major role in startup job choice. Instead, the body of evidence points to non-pecuniary benefits as the driving factor. Of course, workers likely still consider financial aspects when weighing the pros and cons of different job options (see §2.4), and some may still take startup positions in part due to expectations of higher (long-term) income. Second, although startups offer lower earnings and resources for research, they also offer greater opportunities to work on cutting-edge technologies, consistent with our portrayal of the respective R&D portfolios and human capital demands. This result also highlights the value of thinking about a broader range of complementarities between human capital and firm attributes (see §2.2). Third, our results regarding levels of various job attributes as well as self-reported reasons for taking startup employment suggest that preferences related to a broader range of non-pecuniary factors are indeed important to understand why many talented workers chose startup jobs. This, in turn, helps us understand why resource-constrained early-stage startups can select high ability individuals from a relatively large and diverse pool of applicants (§4.4), despite offering lower financial compensation (Stern 2004).

### 4.6 Robustness Checks

Before we conclude, we summarize a series of robustness checks. First, we verified the robustness of our results to different constructions of the dependent variable of startup employment (*Appendix C,* Table C1). Our results are robust to excluding small-established and large-young firms, restricting established firms to the "elite" top 10% in size, and using venture capital data from Crunchbase to exclude growth-stage ventures (Series B or higher). Second, we verified that our results are not an artifact of the construction of relative career preference types by using the baseline career attractiveness measures described in §3.2.3. The results are consistent with the main findings: Individuals who rated startup careers as "attractive" or "extremely attractive" are significantly more likely to work in a startup, while those who rated established firm employment as "attractive" or "extremely attractive" are significantly less likely to work in a startup. Finally, we replicated the main startup employment and earnings analyses controlling for ex post job characteristics and the nature of R&D activities (Table C2), providing more nuanced insights into the role of the type of employer rather than the content of the job per se. The results for ability and career preferences remain substantively unchanged, supporting our premise that firm types (i.e., startups vs. established firms) are a useful level of analysis.

## 5 Discussion

Early-stage startups require talented scientists and engineers to commercialize new technologies. However, these individuals have many outside options, especially in established firms that offer greater complementary assets and higher pay. Although theories of job choice that focus on productivity and income suggest that resource-constrained startups will struggle to hire high ability workers, longitudinal data from a cohort of PhD graduates show the opposite: startups are able to hire high ability scientists and engineers despite paying approximately 20% less than established firms. Consistent with theories of preference-based sorting, we find that many PhDs who join startups expressed career preferences during graduate school startup employment, suggesting that they receive non-pecuniary benefits that compensate them for lower startup pay. Moreover, the pool of applicants is large enough that startups are able to make job offers selectively to the most talented scientists and engineer. Our analyses account for a broad range of controls and the results are robust to using alternative measures and specifications.

Despite these novel findings, our analysis is not without limitations. First, our sample of early-career PhDs is relatively homogenous with respect to age, experience, and education. Although this allowed for a sharper focus on the constructs and mechanisms of interest, our sample may not be representative of the broader population of startup employees or of all types of startups. For example, it is conceivable that PhDs receive greater non-pecuniary benefits from work or are more attracted to working on cutting-edge technologies in startups relative to employees with other degrees. Future research could study such differences using data from populations that are more diverse with respect to education and career stage. At the same time, we expect that our findings that employment outcomes are driven by both preferences and ability, and that preference-based benefits may offset opportunity costs for high ability individuals, applies more generally across contexts and different samples.

Second, while our findings suggest that preferences for startup employment play an important role in explaining why high ability workers join startups despite lower pay, we cannot identify all potentially relevant benefits of startup employment. For example, it is conceivable that some individuals choose startup employment based in part on expectations that startup equity will result in great personal wealth if the venture is successful (Elfenbein et al. 2010). That being said, we conceptualized startup employment as entailing a bundle of job attributes and our results suggest that startup career preferences matter even if we cannot identify all of the specific factors that attract individuals to startups.

Third, although our theoretical discussion focused on labor supply, we also considered the implications of firms' demand for high ability workers. Future research could gain even deeper insights by using more fine-grained measures of demand such as open positions in different kinds of jobs, perhaps even at the level of individual firms. Relatedly, we note that our results are based on realized employment outcomes. For example, our finding that a disproportionate share of startup employees are high ability may partly reflect that our sample reflects more promising startups that were successful in hiring. More comprehensive data on the demand side of the labor market – including firms that fail to hire – could be used to examine such potential selection effects related to the quality of firms rather than the ability of workers (Bryan et al. 2022).

In addition to our contributions to the entrepreneurship literature as discussed in the introduction, our study has implications for founders, managers, and policy makers. First, several studies show that attracting and retaining human capital is a critical hurdle for founders in their efforts to build successful ventures (Baron et al. 1996, Hsu 2009, Wasserman 2012). Our results suggest that early-stage technology startups can overcome these challenges by appealing to individuals who have a strong preference for working in an entrepreneurial environment. Although these individuals appear willing to "pay" to work in startups (Stern 2004), this does not necessarily come "free" to their employers. Rather, some of the features that attract workers to startups may need to be managed carefully and may involve costs of their own, such as higher degrees of autonomy.

Second, selection based on preferences suggests that successful startups may face challenges in keeping early employees if growth leads to changes in organizational features and job characteristics away from those that attracted employees to startups in the first place. Similar concerns are raised by large firms' efforts to "acqui-hire" science and engineering human capital by buying startups: It may well be that employees are more likely to leave after an acquisition if they initially joined the startup precisely because they did not have a taste for a corporate environment (Ng and Stuart 2019, Kim 2020). These concerns would provide further justification for efforts to preserve an entrepreneurial culture as startups grow, or to create entrepreneurial units within larger corporations.

Finally, we found that a significant share of individuals with founder or joiner preferences take employment in established firms. Although future research is needed to understand the role these individuals play for their corporate employers, managers may benefit from identifying these individuals to leverage their entrepreneurial interests, as well as to shield firms from potential negative consequences. For example, employees with entrepreneurial preferences may be particularly open to engaging in corporate entrepreneurship, helping firms' efforts to explore new markets and product domains. On the other hand, failure to understand and address employees' entrepreneurial interests may lead to higher turnover, limiting firms' ability to benefit from their human capital and increasing the risk that employees leave to start competing firms (Campbell et al. 2012).

Overall, attention to both employees' ability and career preferences, and to their joint role in shaping employment outcomes, promises to enrich our understanding of many interesting and important issues in the areas of entrepreneurship, innovation, and human capital.

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## Table 1: Summary statistics by type of employment and ex ante career preference (n=2,394)

| | *Employer type* | | *Ex ante career preference* | | | | |
|---|---|---|---|---|---|---|---|
| | Startup | Est. firm | Founder | Joiner | Indifferent | Est. firm | Other |
| **Sample share** | (11.6%) | (88.4%) | (4.1%) | (7.6%) | (41.7%) | (36.6%) | (10.0%) |
| **Startup employment** | 1.00 | 0.00 | 0.27 | 0.24 | 0.11 | 0.08 | 0.12 |
| *Firm size* - Number of employees | 30.10 | 48179.80 | | | | | |
| *Firm age* - Years since founding | 2.74 | 30.14 | | | | | |
| **Starting compensation ($1,000)** | $93.67 | $107.13 | $105.98 | $104.10 | $104.94 | $106.79 | $101.72 |
| **Ability** | | | | | | | |
| *PhD dept. rank (reverse coded)* | -13.36 | -16.80 | -16.97 | -14.72 | -17.41 | -16.08 | -14.42 |
| **Ex ante career preferences** | | | | | | | |
| *Founder types (col %)* - Intend to start own company in the future | 0.10 | 0.03 | - | - | - | - | - |
| *Joiner types (col %)* - Attracted to startup over est. firm job; no founder intention | 0.15 | 0.07 | - | - | - | - | - |
| *Indifferent types (col %)* - Equally attracted to startup and est. firm jobs | 0.41 | 0.42 | - | - | - | - | - |
| *Established firm types (col %)* - Attracted to est. firm over startup job | 0.24 | 0.38 | - | - | - | - | - |
| *Other types (col %)* - Not attracted to startup job or est. firm job | 0.10 | 0.10 | - | - | - | - | - |
| **Ex ante job attribute preferences** | | | | | | | |
| *Risk tolerance (10 pt. scale)* | 2.53 | 2.26 | 2.94 | 2.32 | 2.50 | 2.18 | 1.60 |
| *Autonomy (5 pt. scale)* | 3.99 | 3.86 | 3.98 | 3.96 | 3.93 | 3.75 | 4.00 |
| *Financial pay (5 pt. scale)* | 4.05 | 4.11 | 4.05 | 4.10 | 4.15 | 4.14 | 3.78 |
| *Managerial work activities (5 pt. scale)* | 2.88 | 3.08 | 3.38 | 2.95 | 3.20 | 3.00 | 2.65 |
| *Commercialization work activties (5 pt. scale)* | 3.65 | 3.71 | 4.21 | 3.77 | 3.89 | 3.67 | 2.82 |
| **Demographic characteristics** | | | | | | | |
| *Male (%)* | 0.67 | 0.70 | 0.87 | 0.79 | 0.74 | 0.62 | 0.64 |
| *Married (%)* | 0.46 | 0.40 | 0.48 | 0.44 | 0.41 | 0.40 | 0.41 |
| *Children (%)* | 0.11 | 0.13 | 0.11 | 0.15 | 0.13 | 0.12 | 0.11 |
| *Prior postdoc (%)* | 0.34 | 0.27 | 0.19 | 0.34 | 0.27 | 0.26 | 0.33 |
| *Foreign worker (%)* | 0.16 | 0.33 | 0.31 | 0.18 | 0.37 | 0.29 | 0.23 |
| **Degree field** | | | | | | | |
| *Life sceinces (row%)* | 0.05 | 0.95 | 0.03 | 0.09 | 0.42 | 0.33 | 0.13 |
| *Chemistry (row%)* | 0.17 | 0.83 | 0.01 | 0.08 | 0.40 | 0.39 | 0.12 |
| *Physics (row%)* | 0.10 | 0.90 | 0.04 | 0.08 | 0.42 | 0.31 | 0.15 |
| *Engineering (row%)* | 0.12 | 0.88 | 0.05 | 0.08 | 0.43 | 0.37 | 0.07 |
| *Computer science (row%)* | 0.10 | 0.90 | 0.06 | 0.05 | 0.42 | 0.42 | 0.05 |
| *Other field (row%)* | 0.10 | 0.90 | 0.05 | 0.09 | 0.36 | 0.36 | 0.14 |

**Table 2: Comparison of startup and established firm career preferences**

| Dependent Variable | Startup career preference |
|---|---|
| PhD department rank | 0.105 |
| | (0.077) |
| Risk tolerance | 0.029 |
| | (0.034) |
| Autonomy | 0.343*** |
| | (0.112) |
| Financial pay | -0.283** |
| | (0.116) |
| Managerial work activities | 0.087 |
| | (0.079) |
| Commercialization work activities | 0.343*** |
| | (0.101) |
| Lab encouraged faculty employment | -0.040 |
| | (0.119) |
| Lab encouraged est. firm employment | -0.514*** |
| | (0.117) |
| Lab encouraged startup employment | 0.537*** |
| | (0.111) |
| PhD advisor was founder | 0.336* |
| | (0.200) |
| Male | 0.657*** |
| | (0.064) |
| Foreign-born | 0.765*** |
| | (0.097) |
| Demographic characteristics | Y |
| Degree field FE | Y |
| Job year FE | Y |
| Log-likelihood | -553.785 |
| Observations | 1141 |

NOTES: Logistic regression predicting startup (founder and joiner types combined; 1) or established firm career preferences (0). Indifferent and other types are excluded to focus on theorized career preference types. Coefficients are log odds. Demographic characteristics are marital status and children. Degree field fixed effects for 14 fields of life sciences, chemistry, physics, engineering, and computer science. Job year fixed effects are for year of first job (2010-2016). Robust standard errors clustered on university in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

**Table 3: Employment in early-stage startup vs. established firm**

| Dependent variable | Employment in early-stage startup | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| **Ability** | | | | | |
| *PhD department rank* | 0.297*** | 0.299*** | 0.300*** | 0.212** | |
| | (0.090) | (0.089) | (0.089) | (0.095) | |
| *Ability index* | | | | | 3.073*** |
| | | | | | (1.041) |
| **Career preferences** | | | | | |
| *Founder types* | | 1.081*** | 1.079*** | 1.085*** | 1.061*** |
| | | (0.230) | (0.215) | (0.215) | (0.216) |
| *Joiner types* | | 0.628** | 0.650** | 0.658*** | 0.561** |
| | | (0.249) | (0.256) | (0.250) | (0.255) |
| *Indifferent types* | | Omitted | Omitted | Omitted | Omitted |
| *Established firm types* | | -0.563*** | -0.551*** | -0.547*** | -0.542*** |
| | | (0.147) | (0.152) | (0.159) | (0.162) |
| *Other types* | | -0.171 | -0.117 | -0.187 | -0.133 |
| | | (0.218) | (0.196) | (0.216) | (0.202) |
| **Job attribute preferences** | | | | | |
| *Risk tolerance* | 0.053** | 0.043* | | | |
| | (0.021) | (0.023) | | | |
| *Autonomy* | 0.171* | 0.119 | | | |
| | (0.097) | (0.098) | | | |
| *Financial pay* | -0.086 | -0.057 | | | |
| | (0.111) | (0.113) | | | |
| *Managerial work activities* | -0.167** | -0.193*** | | | |
| | (0.069) | (0.069) | | | |
| *Commercialization work activities* | 0.101* | 0.053 | | | |
| | (0.060) | (0.068) | | | |
| **Entrepreneurial context** | | | | | |
| *Entrepreneurial region (Boston & SF)* | | | | 0.408** | |
| | | | | (0.200) | |
| *PhD advisor founder* | | | | -0.037 | |
| | | | | (0.097) | |
| *Lab encouraged startup employment* | | | | -0.019 | |
| | | | | (0.077) | |
| Demographic characteristics | Y | Y | Y | Y | Y |
| Degree field FE | Y | Y | Y | Y | Y |
| Labor market conditions | Y | Y | Y | Y | Y |
| Log-likelihood | -797.109 | -774.370 | -785.039 | -766.166 | -734.617 |
| Observations | 2394 | 2394 | 2394 | 2371 | 2259 |

NOTES: Logistic regressions predicting employment in an early-stage startup (1 if age <=5 years and size <=50 employees) or established firm (0 if age >5 years and/or size >50 employees). Coefficients are log odds. Demographic characteristics are gender, marital status, children, prior postdoc, foreign worker status. Degree field fixed effects for 14 fields of life sciences, chemistry, physics, engineering, and computer science. Labor market conditions are log annual early-stage VC funding and annual U.S. GDP growth rate. Robust standard errors. clustered on university in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

**Table 4: Joint effects of ability and preference on startup employment**

| | *High ability - Startup types* (1) | *High ability - Est. firm types* (2) | *Low ability - Startup types* (3) | *Low ability - Est. firm types* (4) |
|---|---|---|---|---|
| *High ability - Startup types* | - | 0.280 (p-value = 0.000) | 0.481 (p-value = 0.039) | 0.146 (p-value = 0.000) |
| *High ability - Est. firm types* | 3.567 (p-value = 0.000) | - | 1.715 (p-value = 0.060) | 0.521 (p-value = 0.037) |
| *Low ability - Startup types* | 2.079 (p-value = 0.039) | 0.583 (p-value = 0.060) | - | 0.304 (p-value = 0.000) |
| *Low ability - Est. firm types* | 6.848 (p-value = 0.000) | 1.920 (p-value = 0.037) | 3.293 (p-value = 0.000) | - |

NOTES: Table reports odds ratios of working in a startup from a series of logistic regressions for each featured ability-preference combinations (column title) relative to other ability-preference combinations (rows). For example, high ability startup types (Column 1) have a 3.567 greater odds of working in a startup compared to high ability established firm types. Models also included combinations for average ability and indifferent and other career preference types, as well as controls for demographic characteristics (gender, marital status, children, prior postdoc, foreign worker status), labor market conditions (log annual early-stage VC funding and annual U.S. GDP growth rate), and degree field fixed effects (14 fields of life sciences, chemistry, physics, engineering, and computer science). Robust standard errors clustered on university.

## Table 5: Startup job search stages

| Dependent variable | Applied to startup job | Received startup job offer | Worked in startup | Worked in startup\|choice |
|---|---|---|---|---|
| **Share of DV = 1** | 47.4% | 62.1% | 45.8% | 26.0% |
| | (1) | (2) | (3) | (4) |
| **Ability** | | | | |
| *PhD department rank* | -0.041 | 0.290*** | 0.260** | 0.531*** |
| | (0.087) | (0.099) | (0.127) | (0.173) |
| **Career preferences** | | | | |
| *Founder types* | 0.761** | 0.974* | 0.779** | 0.479 |
| | (0.326) | (0.508) | (0.351) | (0.621) |
| *Joiner types* | 0.493** | 0.262 | 0.610* | 0.646 |
| | (0.224) | (0.265) | (0.320) | (0.534) |
| *Indifferent types* | Omitted | Omitted | Omitted | Omitted |
| *Established firm types* | -0.295** | -0.240 | -0.495** | -0.572 |
| | (0.137) | (0.208) | (0.251) | (0.370) |
| *Other types* | -0.011 | -0.130 | -0.524* | -0.312 |
| | (0.210) | (0.289) | (0.275) | (0.392) |
| Demographic characteristics | Y | Y | Y | Y |
| Degree field FE | Y | Y | Y | Y |
| Labor market conditions | Y | Y | Y | Y |
| Log-likelihood | -891.181 | -403.361 | -247.737 | -136.925 |
| Observations | 1371 | 648 | 402 | 282 |

NOTES: Logistic regressions predicting different stages of the startup job search process. Coefficients are log odds. DV in Model 1 is applied to startup job (1 if yes, 0 if no). DV for Model 2 is received startup job offer (1 if yes, 0 if no) conditional upon applying to a startup job. DV for Model 3 is worked in startup (1 if yes, 0 if no) conditional upon receiving a startup job offer. DV for Model 4 is worked in startup (1 if yes, 0 if no) conditional upon receiving offers for both startup and established firm jobs. Demographic characteristics are gender, marital status, children, prior postdoc, foreign worker status. Labor market conditions are log annual early-stage VC funding and annual U.S. GDP growth rate. Degree field fixed effects for 14 fields of life sciences, chemistry, physics, engineering, and computer science. Robust standard errors. clustered on university in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

## Table 6: Earnings of startup and established firm employees

| Dependent variable | ln(starting pay) | | | | ln(current pay) |
|---|---|---|---|---|---|
| Sample | Full sample | Full sample | Est. firm employees | Startup employees | Employed 5+ years |
| | (1) | (2) | (3) | (4) | (5) |
| Startup employee | -0.159*** | -0.169*** | | | -0.147*** |
| | (0.026) | (0.026) | | | (0.031) |
| **Ability** | | | | | |
| *PhD department rank* | | 0.061*** | 0.066*** | 0.028 | 0.059*** |
| | | (0.010) | (0.012) | (0.022) | (0.012) |
| **Career preferences** | | | | | |
| *Founder types* | | -0.002 | -0.029 | 0.082 | 0.068 |
| | | (0.044) | (0.064) | (0.069) | (0.076) |
| *Joiner types* | | -0.011 | -0.003 | -0.026 | 0.043 |
| | | (0.033) | (0.037) | (0.071) | (0.052) |
| *Indifferent types* | | Omitted | Omitted | Omitted | Omitted |
| *Established firm types* | | 0.002 | -0.001 | 0.045 | -0.039 |
| | | (0.016) | (0.018) | (0.053) | (0.027) |
| *Other types* | | -0.001 | -0.003 | -0.001 | 0.021 |
| | | (0.027) | (0.029) | (0.073) | (0.053) |
| Stock options/equity | 0.152*** | 0.143*** | 0.152*** | 0.072 | 0.166*** |
| | (0.017) | (0.018) | (0.019) | (0.052) | (0.025) |
| Years of work experience | | | | | 0.078*** |
| | | | | | (0.017) |
| Demographic characteristics | Y | Y | Y | Y | Y |
| Degree field FE | Y | Y | Y | Y | Y |
| Labor market conditions | Y | Y | Y | Y | Y |
| $R^2$ | 0.330 | 0.357 | 0.358 | 0.342 | 0.303 |
| Observations | 1506 | 1506 | 1300 | 206 | 986 |

NOTES: OLS regressions of starting pay in first job and current pay. Dependent variable for Models 1-4 is measured from a question in the *employment survey* that asked respondents to report their total starting compensation (including salary and bonuses) in their first job. Model 1 is a baseline specification with control variables and Model 2 includes ability and career preferences. Model 3 restricts the sample to established firm employees and Model 4 restricts the sample to startup employees. Model 5 replaces starting pay as the dependent variable with current pay for workers with at least five years of industry work experience to compare long-term earnings of employees whose first job was in a startup or established firm. Demographic characteristics are gender, marital status, children, prior postdoc, foreign worker status. Degree field fixed effects for 14 fields of life sciences, chemistry, physics, engineering, and computer science. Labor market conditions are log annual early-stage VC funding and annual U.S. GDP growth rate. Robust standard errors clustered on university in parentheses. * p < 0.10; ** p < 0.05; *** p < 0.01.

## Table 7: Ex post job attributes in first job

| **Dependent variable** | R&D resources | Autonomy | Cutting-edge | Intellectually challenging |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Startup employee | -0.640*** | 0.711*** | 0.520*** | 0.450** |
| | (0.162) | (0.110) | (0.140) | (0.190) |
| Degree field FE | Y | Y | Y | Y |
| Job year FE | Y | Y | Y | Y |
| Log-likelihood | -1151.958 | -1770.128 | -1591.382 | -1442.482 |
| Observations | 1059 | 1258 | 1128 | 1128 |

NOTES: Ordered logistic regressions predicting ex post job attributes. Coefficients are ordered log odds. DV in Model 1 is respondents' assessment of their "current level of resources for R&D activities" on a 4-point scale from "extremely insufficient" (1) to "more than sufficient" (4). DV in Model 2 is respondents' assessment of how much influence they have over choosing which R&D projects to work on from "no influence" (1) to "complete influence" (5). Model 3 is respondents' assessment of the extent to which they agreed that their R&D is "cutting-edge (i.e., advanced areas of science and/or technology)" on a 5-point scale from "strongly disagree" (1) to "strongly agree" (5). DV in Model 4 is respondents' assessment of the extent to which they agreed that their current R&D is "intellectually challenging" on a 5-point scale from "strongly disagree" (1) to "strongly agree" (5). Control variables are degree field fixed effects for 14 fields of life sciences, chemistry, physics, engineering, and computer science, and job year fixed effects (2010-2016). Robust standard errors clustered on university in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

**Table 8: Ex post stated reasons for choosing first job**

| **Dependent variable** | Higher compensation | Job security | Career advancement | Cutting-edge projects |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Startup employee | -1.223*** | -1.689*** | -0.089 | 0.648*** |
| | (0.236) | (0.289) | (0.170) | (0.157) |
| Degree field FE | Y | Y | Y | Y |
| Job year FE | Y | Y | Y | Y |
| Log-likelihood | -786.695 | -677.207 | -846.724 | -818.085 |
| Observations | 1237 | 1237 | 1237 | 1237 |

NOTES: Logistic regressions predicting ex post reasons for working in a startup. Coefficients are log odds. Dependent variables are from a question that asked respondents to indicate "very important reasons" for choosing their first job (1 if yes, 0 if no). Control variables are degree field fixed effects for 14 fields of life sciences, chemistry, physics, engineering, and computer science, and job year fixed effects (2010-2016). Robust standard errors clustered on university in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

| | **Startup types:** Greater preference benefits from startup employment | **Established firm types:** Greater preference benefits from established firm employment |
|---|---|---|
| **High ability workers:** Greater productivity benefits from access to resources and complementary assets.<br><br>In greater demand for cutting-edge R&D projects in both startups and established firms | *High ability startup types*<br>Stronger trade-off between opportunity costs (forgoing greater productivity benefits from working in established firm) and preference benefits from working in startup<br><br>Given startup demand for cutting-edge projects:<br>▪ *If the preference benefits are greater than opportunity costs, then most likely to work in a startup*<br><br>▪ *If preference benefits are less than opportunity costs, then less likely to work in a startup than low ability startup types* | *High ability established firm types*<br>Stronger reinforcement between productivity benefits and preference benefits from working in established firm<br><br>Given established firm demand for cutting-edge projects:<br>▪ *Least likely to work in a startup* |
| **Low ability workers:** Lower productivity benefits from access to resources and complementary assets.<br><br>In greater demand for incremental R&D projects in established firms | *Low ability startup types*<br>Weaker trade-off between opportunity costs (forgoing lower productivity benefits from working in established firm) and preference benefits from working in startup<br><br>If startups can hire high ability workers:<br>▪ *Less likely to work in a startup than high ability startup types, but more likely than established firm types*<br><br>If startups cannot hire high ability workers:<br>▪ *More likely to work in a startup than high ability startup types, and more likely than established firm types* | *Low ability established firm types*<br>Weaker reinforcement between productivity benefits and preference benefits from working in established firm<br><br>Given established firm demand for incremental projects:<br>▪ *Less likely to work in a startup than startup types* |

**Figure 1: Predictions for different ability-preference combinations**

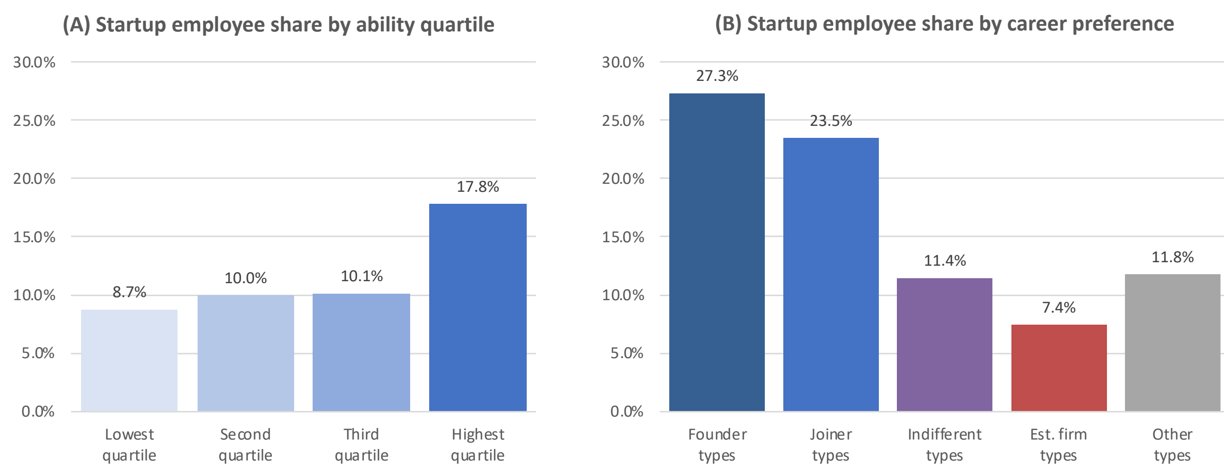


**Figure 2: Share of startup employees by ability quartile (A) and career preferences (B)**

| | Startup type | Indifferent type | Est. firm type |
|---|---|---|---|
| High ability | 29.6% | 18.0% | 11.1% |
| Avg. ability | 21.5% | 10.1% | 6.1% |
| Low ability | 17.4% | 9.7% | 6.2% |

**Figure 3: Predicted probability of working in an early-stage startup by ability-preference combination**

Notes: Predicted probabilities are from a logistic regression that replaces separate ability and career preference variables with categorical variables of each ability-preference combination (e.g., high ability startup type). Ability categories are based on quartiles of PhD department rank: high ability (76-100%), average ability (26-75%), low ability (1-25%). Startup type combines founder and joiner types. Model also includes controls for demographic characteristics (gender, marital status, children, prior postdoc, foreign worker status), degree field fixed effects (14 fields of life sciences, chemistry, physics, engineering, and computer science), and labor market conditions (log annual early-stage VC funding and annual U.S. GDP growth rate).

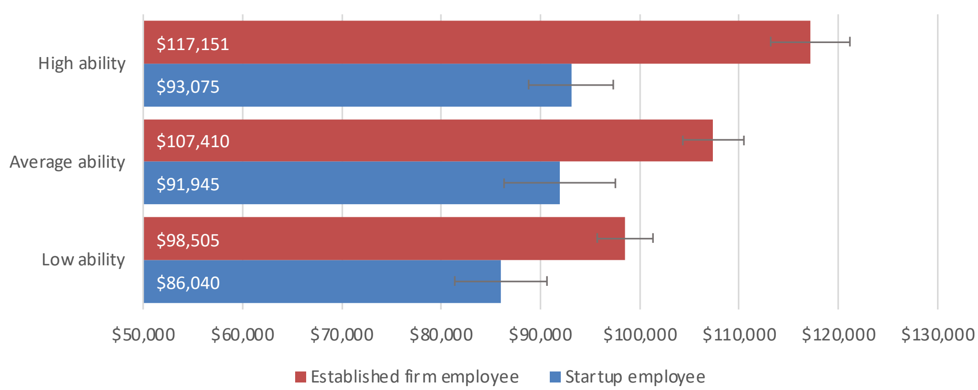


**Fig. 4: Predicted starting earnings by ability and employment**

Notes: Predicted starting pay from an OLS regression of starting pay. Ability categories are based on quartiles of PhD department rank: high ability (76-100%), average ability (26-75%), low ability (1-25%). Model also includes controls for demographic characteristics (gender, marital status, children, prior postdoc, foreign worker status), degree field fixed effects (14 fields of life sciences, chemistry, physics, engineering, and computer science), labor market conditions (log annual early-stage VC funding and annual U.S. GDP growth rate), and stock options.

## Can Early-Stage Startups Hire Talented Scientists and Engineers?
## Ability, Preferences, and Employee Job Choice

# Appendices

**Appendix A – Supplemental analyses**

- A1 – Selection into industry employment
- A2 – Relationship between ability measure and starting earnings
- A3 – Correlates of career preferences
- A4 – Ex ante expectations of job attributes in startups vs. established firms
- A5 – Contingency table analysis: ability quartiles vs. career preferences

**Appendix B – Alternative individual-level ability measures**

- B1 – Replication of main results using ability index

**Appendix C – Robustness tests**

- C1 – Different measures of startup employment and preferences
- C2 – Controlling for ex post job attributes

# Appendix A – Supporting analyses

## Table A1: Selection into industry employment

| **Dependent variable** | Employment in industry (1) or academia (0) | |
|---|---|---|
| | (1) | (2) |
| **Ability** | | |
| *PhD department rank* | 0.077 | 0.079 |
| | (0.073) | (0.073) |
| **Career preferences** | | |
| *Attractiveness of startup career* | | 0.200*** |
| | | (0.040) |
| *Attractiveness of est. firm career* | | 0.357*** |
| | | (0.045) |
| *Attractiveness of research faculty career* | | -0.328*** |
| | | (0.033) |
| **Job attribute preferences** | | |
| *Risk tolerance* | 0.007 | 0.003 |
| | (0.012) | (0.012) |
| *Autonomy* | -0.434*** | -0.253*** |
| | (0.048) | (0.047) |
| *Financial pay* | 0.341*** | 0.203*** |
| | (0.045) | (0.050) |
| *Managerial work activities* | 0.035 | 0.014 |
| | (0.029) | (0.032) |
| *Basic research work activities* | -0.258*** | -0.147*** |
| | (0.035) | (0.037) |
| *Applied research work activities* | 0.115** | 0.031 |
| | (0.059) | (0.061) |
| *Commercialization work activities* | 0.277*** | 0.136*** |
| | (0.031) | (0.032) |
| Demographic characteristics | Y | Y |
| University lab context | Y | Y |
| Degree field FE | Y | Y |
| University FE | Y | Y |
| Log-likelihood | -3102.018 | -2973.381 |
| Observations | 5486 | 5486 |

NOTES: Logistic regressions predicting whether PhD graduates transitioned to industrial R&D occupations (sample for this study; 1) or remained in academia (tenure-track, non-tenure track, or postdoc; 0). Attractiveness of startup, established firm, and faculty research careers measured separately on a 5-point Likert scale from "extremely unattractive" (0) to "extremely attractive" (1). Demographic characteristics are gender, marital status, children, foreign-born. University lab context variables are whether the department encouraged careers in industry or academia, respectively, and whether their advisor had founded a company. Degree field fixed effects for 14 fields of life sciences, chemistry, physics, engineering, and computer science. University fixed effects for 37 universities in our sample. Robust standard errors clustered on university in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

## Table A2: Relationship between ability measure and starting earnings

| Dependent variable | ln(starting pay) | |
|---|---|---|
| | (1) | (2) |
| **Ability** | | |
| *PhD department rank* | 0.060*** | |
| | (0.008) | |
| *Highest PhD dept. rank quartile* | | 0.141*** |
| | | (0.024) |
| *Third PhD dept. rank quartile* | | 0.094*** |
| | | (0.027) |
| *Second PhD dept. rank quartile* | | 0.069*** |
| | | (0.017) |
| *Lowest PhD dept. rank quartile* | | Omitted |
| **Firm characteristics** | | |
| *Size* | 0.039*** | 0.039*** |
| | (0.005) | (0.005) |
| *Age* | -0.022* | -0.023* |
| | (0.012) | (0.012) |
| *Employer stock options* | 0.112*** | 0.113*** |
| | (0.021) | (0.020) |
| **Individual characteristics** | | |
| *Male* | 0.088*** | 0.088*** |
| | (0.014) | (0.014) |
| *Married* | -0.004 | -0.004 |
| | (0.017) | (0.017) |
| *Children* | 0.003 | 0.000 |
| | (0.018) | (0.018) |
| *Prior postdoc* | 0.014 | 0.014 |
| | (0.014) | (0.014) |
| *Foreign-born* | 0.013 | 0.010 |
| | (0.019) | (0.020) |
| Degree field FE | Y | Y |
| Job year FE | Y | Y |
| $R^2$ | 0.412 | 0.408 |
| Observations | 1224 | 1224 |

NOTES: OLS regressions to examine the extent to which PhD department rank explains variation in starting pay. Sample is industry R&D employees who responded to the *employment survey*. The dependent variable is ln(starting pay) measured from a survey question that asked respondents to report their total starting compensation (including salary and bonuses) in their first job. Model 2 uses PhD department rank quartiles to examine the directionality and magnitude of the relationship for different categorical levels of ability. Firm size (number of employees) and age (years since founding) are based on survey questions about first employer or from matched LinkedIn data. Degree field fixed effects for 14 fields of life sciences, chemistry, physics, engineering, and computer science. Job year fixed effects are for year of first job (2010-2016). Robust standard errors clustered on university in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

## Table A3: Correlates of career preferences

| Dependent Variable | Founder intentions | Attractiveness of startup career | Attractiveness of est. firm career | Startup types (1) vs. est. firm types (0) |
|---|---|---|---|---|
| **Method** | Ordered logit | Ordered logit | Ordered logit | Logit |
| | (1) | (2) | (3) | (4) |
| PhD department rank | 0.011 | -0.025 | -0.123** | 0.105 |
| | (0.049) | (0.040) | (0.060) | (0.077) |
| Risk tolerance | 0.096*** | 0.040** | 0.019 | 0.029 |
| | (0.019) | (0.019) | (0.019) | (0.034) |
| Autonomy | 0.379*** | 0.210*** | -0.108* | 0.343*** |
| | (0.050) | (0.054) | (0.061) | (0.112) |
| Financial pay | -0.116** | 0.254*** | 0.560*** | -0.283** |
| | (0.059) | (0.063) | (0.071) | (0.116) |
| Managerial work activities | 0.265*** | 0.038 | -0.048 | 0.087 |
| | (0.046) | (0.051) | (0.038) | (0.079) |
| Commercialization work activities | 0.482*** | 0.686*** | 0.578*** | 0.343*** |
| | (0.041) | (0.064) | (0.056) | (0.101) |
| Lab encouraged faculty employment | -0.006 | -0.041 | 0.022 | -0.040 |
| | (0.048) | (0.066) | (0.052) | (0.119) |
| Lab encouraged est. firm employment | -0.198** | -0.233*** | 0.292*** | -0.514*** |
| | (0.093) | (0.080) | (0.074) | (0.117) |
| Lab encouraged startup employment | 0.275*** | 0.337*** | -0.247*** | 0.537*** |
| | (0.078) | (0.084) | (0.086) | (0.111) |
| PhD advisor was founder | 0.144 | 0.068 | -0.012 | 0.336* |
| | (0.112) | (0.126) | (0.110) | (0.200) |
| Male | 0.988*** | 0.633*** | -0.179** | 0.657*** |
| | (0.181) | (0.090) | (0.087) | (0.064) |
| Foreign-born | 0.372** | 0.142 | 0.241*** | 0.765*** |
| | (0.162) | (0.102) | (0.093) | (0.097) |
| Demographic characteristics | Y | Y | Y | Y |
| Degree field FE | Y | Y | Y | Y |
| Job year FE | Y | Y | Y | Y |
| Log-likelihood | -2770.459 | -2857.064 | -2424.471 | -553.785 |
| Observations | 2243 | 2359 | 2359 | 1141 |

NOTES: Results examine association between ex ante career preference measures and stated job attribute preferences, social context, and demographic characteristics. DV in Model 1 is respondents' expectations of their likelihood of starting their own company on a 5-point scale from "definitely will not" (1) to "definitely will" (5). DV in Model 2 is the attractiveness of a career "in a startup firm with an emphasis on research or development" on a 5-point scale from "extremely unattractive" (1) to "extremely attractive" (5). DV in Model 3 is that attractiveness of a career "in an established firm with an emphasis on research or development" on a 5-point scale from "extremely unattractive" (1) to "extremely attractive" (5). DV in Model 4 is startup types (founder and joiner types combined; 1) vs. established firm types (0). DV in Model 5 is indifferent types (1) vs. established firm types (0). Demographic characteristics are gender, marital status, children, foreign-born. Degree field fixed effects for 14 fields of life sciences, chemistry, physics, engineering, and computer science. Job year fixed effects are for year of first job (2010-2016). Robust standard errors clustered on university in parentheses. * p < 0.10; ** p < 0.05; *** p < 0.01.

**Table A4: Ex ante expectations of job attributes in startups vs. established firms**

| | Startup | Est.firm | Obs. | t-statistic | p-value |
|---|---|---|---|---|---|
| Starting salary ($1,000) | $79.0 | $94.1 | 2009 | -24.34 | 0.00 |
| Autonomy ("high" or "extremely high") | 22.2% | 6.8% | 2005 | 11.05 | 0.00 |
| Intellectual challenge ("high" or "extremely high") | 79.4% | 59.8% | 595 | 10.67 | 0.00 |
| R&D resources ("high" or "extremely high") | 21.4% | 67.1% | 558 | -15.37 | 0.00 |
| Job security ("high" or "extremely high") | 3.9% | 44.3% | 563 | -28.44 | 0.00 |

NOTES: Mean comparisons of expectations of different job attributes in startup and established firms. Survey questions asked PhD students about “starting total annual compensation” (in USD), and availability of “freedom to choose research projects”, intellectually challenging work”, “research funds”, and “job security” (all reported in share of respondents who indicated “high” or “extremely high” availability).

## Table A5: Contingency table analysis: ability quartiles vs. career preferences

| | Ability quartile | | | | |
|---|---|---|---|---|---|
| | 1st | 2nd | 3rd | 4th | Total |
| **Founder types** | 27 | 23 | 29 | 20 | 99 |
| | 27.27 | 23.23 | 29.29 | 20.20 | 100.00 |
| | 4.20 | 3.72 | 4.98 | 3.45 | 4.08 |
| **Joiner types** | 38 | 47 | 47 | 51 | 183 |
| | 20.77 | 25.68 | 25.68 | 27.87 | 100.00 |
| | 5.91 | 7.59 | 8.08 | 8.79 | 7.55 |
| **Indifferent types** | 286 | 272 | 233 | 220 | 1,011 |
| | 28.29 | 26.90 | 23.05 | 21.76 | 100.00 |
| | 44.48 | 43.94 | 40.03 | 37.93 | 41.71 |
| **Est. firm types** | 233 | 214 | 220 | 219 | 886 |
| | 26.30 | 24.15 | 24.83 | 24.72 | 100.00 |
| | 36.24 | 34.57 | 37.80 | 37.76 | 36.55 |
| **Other types** | 59 | 63 | 53 | 70 | 245 |
| | 24.08 | 25.71 | 21.63 | 28.57 | 100.00 |
| | 9.18 | 10.18 | 9.11 | 12.07 | 10.11 |
| **Total** | 643 | 619 | 582 | 580 | 2,424 |
| | 26.53 | 25.54 | 24.01 | 23.93 | 100.00 |
| | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |

Pearson $c^2(12) = 14.4445$ Pr = 0.273

NOTE: Contingency table of ex ante career preference types by ability quartiles (PhD department rank). First number in each cell is the frequency, followed by row percentage and then column percentage. Pearson $\chi^2$ is a test of the independence between the observed frequencies of career preferences and ability in each cell. The $\chi^2$ value of 14.445 fails to reject the null hypothesis that career preferences and ability are independent.

# Appendix B – Alternative individual-level ability measure

A potential limitation of our featured proxy of ability (PhD department rank) is that it does not vary across individuals within a given department. To check the robustness of our results to this limitation, we constructed an alternate individual-level ability measure that builds on an approach used in prior studies that is based on the assumption that, all else held constant, higher ability workers earn higher pay (see, for example, Farber and Gibbons 1996, Gibbons et al. 2005). Given that ability is typically unobserved by the econometrician, this work typically first regresses worker pay onto observed determinants of pay such as industry, employer size, occupation, and individual worker demographic characteristics such as gender and age. The remaining unexplained variance in pay reflects unobserved variables associated with pay, including unobserved ability. This model is then used to predict expected pay based on observables and the residual is used as a proxy for unobserved ability. A limitation of this approach, however, is that the residual reflects not only unobserved ability but also all other unobserved variables, such as preferences.

We modify this approach in two ways. First, we start with the premise that first-time employees exhibit signals of their ability during their job search that are used by employers to make decisions about job offers and starting pay. In our context of science and engineering PhDs in R&D occupations, these signals include publications and conference proceedings, patents, research awards, and the quality of the PhD degree program (NRC department rank). Although prior studies typically do not observe such ability signals, our survey provides responses that we can use as correlates of ability.

Second, rather than proxying for unobserved ability using the residual from a wage regression, we instead use predicted values from a model that regresses starting pay onto our measures of ability signals. We exclude employer and job characteristics from this model such that by construction they are captured in the error term. More formally, our model is $W_i = \alpha + \beta A_i + \varepsilon_i$, where $W_i$ is starting pay, $\alpha$ reflects average starting pay, $A_i$ is a vector of observable ability signals that predict variation in starting pay, and $\varepsilon_i$ is the error term. In this way, we separate the component of starting pay attributable to observable ability signals, $\beta$ in our model, from the component of starting pay attributable to job and employer characteristics, which is captured in the error term.

To improve the precision of our model, we also control for individual characteristics including degree field, gender, citizenship, postdoc experience, and year of first job given that these variables are likely correlated with both starting pay and observable ability signals but should themselves be unrelated with true ability.[1] For example, computer science PhDs may have fewer publications and earn higher pay than immunology PhDs for reasons related to their degree field and not ability. We also estimated this model using only ability signals without these controls with substantively identical results.

Using estimates from this model, we calculated predicted values for the contribution of ability signals to starting pay for each individual. We label this variable *ability index*. We do not include the control variables (e.g., gender, degree field, etc.), the constant (i.e., average starting salary), or job or employer characteristics (i.e., captured in the residual) in our calculation.[2] As such, *ability index* reflects the expected individual-level variation in pay due to workers' observed number of publications and conference proceedings (combined), patents, research awards, and PhD degree program quality regardless of whether they work in a startup or established firm. Given that *ability index* is calculated based on ex ante observables from the *PhD survey*, we can compute it for our full sample (i.e., out-of-sample predictions for individuals who did not respond to the *employment survey* and for whom we do not observe starting pay).

[1] We acknowledge that postdoc experience may be related with ability either because of selection into postdoc training or because such training helps build relevant skills and knowledge. Any such ability would still be reflected in our predicted ability measure (see below). An alternative version of this approach excluding the postdoc variable yields the same substantive results.
[2] The results are the same when we include the control variables in the predicted values.

We recognize that in addition to reflecting individual ability, starting pay also differs systematically across firm types (see §2.1). As noted above, we address this concern by excluding firm characteristics from the regression such that they are captured in the error term and not *ability index*. In addition, we constructed *ability index* using estimates from both the full sample as well as a restricted sample that excludes startup employees since they may be paid less for reasons other than their ability, such as a taste-based wage discount (i.e., we estimated the model based on the 88% of workers in established firms who represent the dominant market). Both samples yield the same substantive results, and we report the more restricted version both to reduce the potential confounding role of firm characteristics and because data from established firms arguably provide better insights into ability wage premia given that established firms have greater resources to compensate workers for their higher ability (see §4.5.1). We do not claim that *ability index* is a perfect measure of ability, but rather that it is a useful individual-level proxy to examine the robustness of our ability findings.

Table B1 presents the model used to estimate the contribution of ability signals to starting pay in Column 1. As expected, the observed ability signals are all significant: PhDs with higher levels of these ability signals earn more than otherwise comparable graduates in their field, regardless of their employer or job. To put these estimates into perspective, a one standard deviation change in the independent variables increases the average starting pay by 2.5% for publications and conference proceedings, 3.3% for patents, 1.4% for research awards, and 6.6% for PhD department rank. The significance of these results suggest that employers use these signals to determine starting pay.

Columns 2-4 in Table B1 present key regressions using *ability index* in lieu of *PhD department rank* as our measure of ability. The results are remarkably consistent with those using PhD department ranking: Workers with a higher ability index are more likely to work in a startup and are more likely to receive a startup job offer, but are not more likely to apply to a startup job. The coefficient estimates for career preferences are nearly identical to the results using PhD department ranking, indicating that they are not sensitive to the ability measure used.

**Table B1: Replication of main results using ability index**

| | | Startup | Applied to | Received | Startup |
|---|---|---|---|---|---|
| **Dependent variable** | ln(starting pay) | employment | startup job | startup job offer | employment |
| **Method** | OLS | Logit | Logit | Logit | Logit |
| | (1) | (2) | (3) | (4) | (5) |
| ln(publications+proceedings) | 0.034*** | | | | |
| | (0.011) | | | | |
| ln(patents) | 0.090*** | | | | |
| | (0.024) | | | | |
| ln(academic awards) | 0.022*** | | | | |
| | (0.005) | | | | |
| PhD department rank | 0.071*** | | | | |
| | (0.012) | | | | |
| Ability index | | 3.226*** | -0.088 | 3.658*** | 2.987* |
| | | (1.021) | (0.877) | (0.920) | (1.547) |
| **Career preferences** | | | | | |
| *Founder types* | | 1.083*** | 0.744** | 0.900* | 0.816** |
| | | (0.220) | (0.323) | (0.505) | (0.362) |
| *Joiner types* | | 0.524** | 0.447* | 0.135 | 0.529* |
| | | (0.252) | (0.230) | (0.270) | (0.312) |
| *Indifferent types* | | Omitted | Omitted | Omitted | Omitted |
| *Established firm types* | | -0.560*** | -0.309** | -0.250 | -0.475* |
| | | (0.168) | (0.131) | (0.207) | (0.275) |
| *Other types* | | -0.127 | 0.010 | -0.202 | -0.268 |
| | | (0.198) | (0.222) | (0.305) | (0.268) |
| Demographic characteristics | Y | Y | Y | Y | Y |
| Degree field FE | Y | Y | Y | Y | Y |
| Job year FE | Y | Y | Y | Y | Y |
| $R^2$ | 0.336 | | | | |
| Log-likelihood | | -733.369 | -850.050 | -376.322 | -235.831 |
| Observations | 1248 | 2264 | 1312 | 619 | 387 |

NOTES: Model 1 estimates the contribution of ability signals to starting pay, labeled *ability index*, using the sample from the *employment survey*. Estimates from this model are used to predict individual ability for the full sample, while excluded job and employer characteristics which are captured in the residual. *Ability index* is used in Models 2-4 in lieu of *PhD department rank* as the ability measure. Models 2 replicates the results in Table 3. Models 3 and 4 replicate the results in Table 5. Demographic characteristics are gender, marital status, children, foreign-born and postdoc experience. Degree field fixed effects included for 14 fields of life sciences, chemistry, physics, engineering, and computer science. Job year fixed effects are for year of first job (2010-2016). Robust standard errors clustered on university in parentheses. * p < 0.10; ** p < 0.05; *** p < 0.01.

# Appendix C – Robustness checks

Table C1 reports robustness checks for our results to different estimation methods and construction of dependent and independent variables. First, Model 1 replicates our preferred model of startup employment (Table 2, Model 3) using a linear probability model.

Next, we examine the robustness of our results to different constructions of the dependent variable of startup employment. Model 2 uses an alternate dependent variable that excludes small-established (older than 10 years and less than 500 employees) and large-young (younger than 10 years and more than 500 employees, e.g., growth-stage ventures and corporate spinoffs) firms to draw a clearer distinction between employment in early-stage startup vs. large established firms. While the coefficient of PhD department rank is virtually unchanged, the coefficient of joiner preferences is somewhat larger than in the full sample, as one might expect. Model 3 further refines the dependent variable to restrict established firms to the top 10% in size (in our sample, over 100,000 employees) to focus on "elite" firms. We also included Google in this sample since it employed the most PhDs in our sample (140) even though it had only 72,000 employees in 2016. We find that ability and career preferences remain significant predictors of startup employment, although the coefficient of PhD department rank is notably smaller than in the main model. Thus, early-stages startups still fare well in recruiting high ability individuals compared to the largest established firms with the greatest resources and reputation, but their "advantage" is somewhat reduced compared to established firms more generally. Model 4 uses Crunchbase data to construct an alternate dependent variable where early-stage startups are classified as pre-funding through Series A ("early-stage VC funding") compared to all other firms (including growth-stage VC-funded firms). This regression verifies that our results hold if we exclude any early-stage startups that may have raised more significant funding (and, thus, conform less to the description of early-stage startups laid out in §2.1).

Finally, we examine the robustness of our results to a different construction of career preferences. Model 5 uses the same dependent variable as the main results but replaces career preference types used in the featured results with the baseline survey measures of the attractiveness of careers in a startup and an established firm; the omitted categories are individuals who rated a career as not attractive (1-3). The qualitative results are robust.

Table C2 addresses the possibility that graduates' employment choices, as well as earnings differences, may reflect differences in job attributes between startups and established firms that are unrelated to startup career preferences. Although it is difficult to draw a clear conceptual (and empirical) distinction between characteristics of the employer and the job (see $2.1), we re-estimate our key regressions of startup employment and earnings with additional controls (Table C2, Models 1-4). In particular, we draw on questions from the *employment survey* to control for a range of job attributes: level of R&D resources, autonomy, the extent to which R&D is cutting-edge and intellectually challenging, respectively, number of hours worked (six self-reported categories) and the share of time devoted to each of 4 different work activities such as basic research and management (four categories each). Columns 1 and 3 present the baseline results without controls for job attributes, while Columns 2 and 4 include these controls. The results for ability and career preferences are robust to controlling for job attributes.

**Table C1: Different measures of startup employment and preferences**

| **Dependent variable** | Eartly-stage Startup | Early-stage vs. Large est. firms | Early-stage vs. top 10% est. firms | Early-stage VC funding | Eartly-stage Startup |
|---|---|---|---|---|---|
| **Method** | LPM | Logit | Logit | Logit | Logit |
| | (1) | (2) | (3) | (4) | (5) |
| **Ability** | | | | | |
| *PhD department rank* | 0.029*** | 0.296*** | 0.187** | 0.303*** | 0.291*** |
| | (0.009) | (0.100) | (0.093) | (0.096) | (0.089) |
| **Career preferences** | | | | | |
| *Founder types* | 0.148*** | 1.084*** | 0.628* | 1.085*** | |
| | (0.037) | (0.246) | (0.346) | (0.223) | |
| *Joiner types* | 0.096** | 0.851*** | 0.871** | 0.664** | |
| | (0.040) | (0.299) | (0.441) | (0.267) | |
| *Indifferent types* | Omitted | Omitted | Omitted | Omitted | |
| *Established firm types* | -0.045*** | -0.570*** | -0.633*** | -0.568*** | |
| | (0.013) | (0.160) | (0.188) | (0.162) | |
| *Other* | -0.011 | -0.111 | -0.293 | -0.155 | |
| | (0.020) | (0.226) | (0.362) | (0.207) | |
| **Career attractiveness** | | | | | |
| *Startup attractive (4)* | | | | | 0.600*** |
| | | | | | (0.187) |
| *Startup extremely attractive (5)* | | | | | 1.119*** |
| | | | | | (0.203) |
| *Est. firm attractive (4)* | | | | | -0.504** |
| | | | | | (0.204) |
| *Est. firm extremely attractive (5)* | | | | | -1.113*** |
| | | | | | (0.256) |
| Demographic characteristics | Y | Y | Y | Y | Y |
| Degree field FE | Y | Y | Y | Y | Y |
| Labor market conditions | Y | Y | Y | Y | Y |
| $R^2$ | .064 | | | | |
| Log-likelihood | | -676.345 | -356.777 | -761.700 | -786.962 |
| Observations | 2407 | 1875 | 763 | 2407 | 2407 |

NOTES: Regression analyses examining robustness of results to different estimation methods and construction of dependent and independent variables. Demographic characteristics include gender, marital status, children, prior postdoc, foreign worker status. Degree field fixed effects for 14 fields of life sciences, chemistry, physics, engineering, and computer science. Labor market conditions include log annual early-stage VC funding and annual U.S. GDP growth rate. Robust standard errors clustered on university in parentheses. * p < 0.10; ** p < 0.05; *** p < 0.01.

## Table C2: Controlling for ex post job attributes

| **Dependent variable** | Startup employment | | ln(starting pay) | |
|---|---|---|---|---|
| **Method** | Logit | Logit | OLS | OLS |
| | (1) | (2) | (3) | (4) |
| **Ability** | | | | |
| *PhD department rank* | 0.385*** | 0.357*** | 0.067*** | 0.062*** |
| | (0.118) | (0.125) | (0.010) | (0.009) |
| **Career preferences** | | | | |
| *Founder types* | 1.048*** | 0.922** | 0.023 | 0.011 |
| | (0.327) | (0.366) | (0.057) | (0.060) |
| *Joiner types* | 0.750** | 0.689* | -0.004 | 0.001 |
| | (0.345) | (0.368) | (0.037) | (0.037) |
| *Indifferent types* | Omitted | Omitted | Omitted | Omitted |
| *Established firm types* | -0.473** | -0.508* | -0.005 | -0.011 |
| | (0.240) | (0.273) | (0.018) | (0.017) |
| *Other types* | -0.252 | -0.295 | -0.025 | -0.035 |
| | (0.353) | (0.377) | (0.031) | (0.029) |
| **Job attributes** | | | | |
| *Level of R&D resources* | | -0.691*** | | 0.057*** |
| | | (0.147) | | (0.011) |
| *Autonomy* | | 0.288*** | | 0.025*** |
| | | (0.092) | | (0.009) |
| *R&D is cutting-edge* | | 0.344*** | | -0.003 |
| | | (0.074) | | (0.009) |
| *R&D is intellectually challenging* | | 0.249 | | 0.009 |
| | | (0.168) | | (0.011) |
| *Hours worked* | | 0.012 | | 0.003** |
| | | (0.015) | | (0.002) |
| *Basic research* | | -0.068 | | 0.003 |
| | | (0.083) | | (0.012) |
| *Applied research* | | -0.115 | | 0.005 |
| | | (0.117) | | (0.009) |
| *Development* | | 0.122 | | -0.003 |
| | | (0.115) | | (0.009) |
| *Management* | | 0.052 | | 0.002 |
| | | (0.144) | | (0.010) |
| **Startup employee** | | | -0.163*** | -0.158*** |
| | | | (0.037) | (0.033) |
| Demographic characteristics | Y | Y | Y | Y |
| Degree field FE | Y | Y | Y | Y |
| Labor market conditions | Y | Y | Y | Y |
| Log-likelihood | -344.353 | -317.233 | | |
| $R^2$ | | | 0.352 | 0.385 |
| Observations | 958 | 958 | 935 | 935 |

NOTES: Regression analyses examining robustness of results to controlling for ex post job attributes. *Level of R&D resources* is respondents' assessment of their "current level of resources for R&D activities" on a 4-point scale from "extremely insufficient" (1) to "more than sufficient" (4). *Autonomy* is respondents' assessment of how much influence they have over choosing which R&D projects to work on from "no influence" (1) to "complete influence" (5). *R&D is cutting-edge* is respondents' assessment of the extent to which they agreed that their R&D is "cutting-edge (i.e., advanced areas of science and/or technology)" on a 5-point scale from "strongly disagree" (1) to "strongly agree" (5). *R&D is intellectually challenging* is respondents' assessment of the extent to which they agreed that their current R&D is "intellectually challenging" on a 5-point scale from "strongly disagree" (1) to "strongly agree" (5). *Hour worked* "during a typical week" measured in 10-hour increments (e.g., 40-49 hours, 50-59 hours, etc.). Other job attributes are based on a question that asked "During a typical workweek, what percentage of your time do you spend on the following activities?" where responses were 0%, 1-10%, 11-40%, and 41-100%. Activities are: "Research that contributes fundamental insights or theories (basic research)", "Research that creates knowledge to solve practical problems (applied research)", "Using knowledge to develop materials, devices, or software (development)", and "Managing projects or people". Demographic characteristics include gender, marital status, children, prior postdoc, foreign worker status. Degree field fixed effects for 14 fields of life sciences, chemistry, physics, engineering, and computer science. Labor market conditions include log annual early-stage VC funding and annual U.S. GDP growth rate. Robust standard errors clustered on university in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

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