ENTREPRENEURSHIP EDUCATION AND CAREER TRAJECTORIES

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Abstract: As entrepreneurship education has become increasingly prevalent in higher education, its broader consequences for students' career development have attracted growing attention. Supporters argue that entrepreneurship programs generate long-term value by cultivating transferable skills that benefit participants beyond venture creation. Critics, however, contend that such programs may crowd out other educational investments and potentially undermine academic and labor market outcomes. Despite ongoing debate over its net impact, existing research has focused primarily on whether entrepreneurship education increases entrepreneurial activity, leaving its effects on broader career trajectories underexplored. Drawing on ten years of longitudinal data from a university startup incubator, this study examines the impact of an entrepreneurship education program by comparing the post-graduation career trajectories of accepted and rejected applicants. The results show that exposure to entrepreneurship education does not necessarily increase entrepreneurial activity immediately after graduation. However, participation is associated with sustained career advantages, even among students who do not pursue entrepreneurship in the short term. Specifically, participants demonstrate better job matching, as reflected in higher earnings, longer tenure with their initial employers, and greater stability in occupational type. These findings provide empirical evidence that entrepreneurship education can generate enduring positive returns in the broader labor market. They also offer important implications for universities and organizations evaluating whether to invest in entrepreneurship programs, suggesting that the value of such programs extends beyond the creation of new ventures.

Keywords: Entrepreneurship Education; Career Trajectories; Labor Market Outcomes; Job Matching

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I INTRODUCTION

Higher education institutions have increasingly integrated entrepreneurship-focused curricula and initiatives into their educational offerings (Katz, 2003). This proliferation reflects a growing belief that entrepreneurial skills are broadly valuable in modern labor markets, enhancing students' competitiveness while fostering innovation in society. Proponents argue that early exposure to entrepreneurship can be particularly beneficial, often pointing to well-known entrepreneurs who launched ventures while still in school, including the founders of Google, Bill Gates, Mark Zuckerberg, Michael Dell, and the founders of Warby Parker.

Beyond venture creation, entrepreneurship education may also generate broader career benefits by cultivating transferable skills, such as opportunity recognition, risk management, creativity, and resilience, that are valuable across a wide range of career paths (Campbell, 2013; Gompers et al., 2005; Lazear, 2004; Shane, 2003). Anecdotal evidence is consistent with this view. For instance, the Wharton School's inaugural high school entrepreneurship conference, EntreCon '86, illustrates the lasting influence that early entrepreneurial exposure may have on career trajectories. A retrospective study conducted 35 years later found that the program continued to shape participants' careers, including those who ultimately entered conventional professions such as law, investment management, and academia (Drake, 2022). Many participants described the experience as a "guiding beacon" that shaped their approach to work and life, while surveyed attendees reported that it profoundly influenced their career choices, broadened their perspectives on future opportunities, and helped define their passions.

However, introducing entrepreneurship training early in students' educational trajectories may also entail costs. Critics argue that such programs can crowd out investment in traditional academic activities, thereby reducing academic performance and educational attainment. For example, a field experiment evaluating an edutainment television program on entrepreneurship education among secondary school students found that treated students were less likely to continue schooling, without corresponding improvements in entrepreneurial activity (Bjorvatn et al., 2020). These competing perspectives highlight an unresolved debate over the net impact of entrepreneurship education, particularly whether its potential career benefits outweigh the academic and opportunity costs associated with participation.

While there is evidence supporting both sides of the argument, existing research on these programs has focused primarily on their direct effects on entrepreneurial intentions, subsequent entrepreneurial activity, and venture performance (Hsu et al., 2007; Von Graevenitz et al., 2010; Eesley and Lee, 2021), leaving aside a large and arguably more representative group: individuals who receive entrepreneurship education but ultimately pursue careers in wage employment. As a result, it remains unclear whether entrepreneurship education

shapes students' longer-term career trajectories beyond entrepreneurial entry, including the quality, stability, and economic returns of their post-graduation employment.

To answer this question, we examine the career outcomes of individuals who participated in a long-standing entrepreneurship initiative at a leading technology-based university. Established over a decade ago, the program has provided an immersive summer experience in venture creation, supported by seed funding and intensive mentorship. The initiative is designed to be broadly inclusive, drawing participants not only from students at all academic levels but also from faculty, researchers, and alumni. Specifically, we analyze how engagement in entrepreneurship education is associated with individuals' initial career choices following program participation, including the likelihood of pursuing entrepreneurial activities versus wage employment. We further examine career fit in individuals' first full-time job, conditional on choosing wage employment as their initial career path. Our sample includes cohorts of applicants from 2014, when the program was first launched, through 2023. We draw on administrative records from the program, including an application dataset documenting all applicants and their admission status, as well as a participation dataset identifying those who ultimately took part in the program as startup founders. We manually link these individuals to their online résumé profiles and extract their job histories to construct post-program career trajectories, observed through April 2024. Our data allow us to complement and extend the existing literature in several important ways. First, the university-wide nature of the program enables us to capture entrepreneurial engagement among a broad and diverse student population, rather than among students selected from specific colleges, majors, or entrepreneurship courses. Second, the longitudinal structure of the data allows us to examine participants' actual post-program career paths and labor market outcomes, complementing prior work that often relies on shorter-term measures such as entrepreneurial intentions or immediate startup outcomes. Third, résumé-based career histories allow us to observe realized career trajectories with greater granularity than self-reported survey data, including job transitions, employer tenure, occupational choices, and earnings-related indicators.

The study provides empirical evidence on the effect of the entrepreneurship program on later career trajectories by comparing program participants with applicants who were not admitted, as both groups demonstrate strong entrepreneurial motivation. Our findings indicate no significant difference between program participants and non-admitted applicants in the likelihood of entering self-employment in the first full-time job after program completion. This suggests that entrepreneurship education may be valuable in a dimension beyond increasing the likelihood of venture success: it may help participants assess their fit with entrepreneurship. Among those who initially enter wage employment, we examine compen-

sation in the initial job and analyze initial career transitions using survival models, which capture two dimensions of early career progression: tenure with the initial employer and tenure in the initial occupation. Compared with non-admitted applicants, program participants earn 8.27% higher salaries in their first jobs. They also exhibit longer tenure with their first employer and in their initial occupation type. This pattern is consistent with improved career fit and progression among participants, reflecting better initial job matches and greater early-career retention. The salary premium is stronger among individuals with greater industry exposure prior to the program. Our results remain robust across matching analyses, double machine learning methods, instrumental-variable analysis, alternative compensation outcome measures, and several sensitivity checks.

The remainder of the paper is organized as follows. Section 2 provides background on entrepreneurship education, relevant literature, and hypothesis development. Section 3 introduces the research context, data sources, and variable measurements. Section 4 presents the baseline empirical models. Section 5 reports the main results. Section 6 presents robustness checks. Section 7 concludes by discussing the implications of the findings, limitations, and directions for future research.

II BACKGROUND AND HYPOTHESES DEVELOPMENT

II.A General Background and Research on Entrepreneurship Education

Entrepreneurship education has been widely adopted in universities and corporate training programs (Vesper and Gartner, 1997; Cumming and Fischer, 2012). These programs are typically organized as structured learning offerings that combine entrepreneurship-related content with practice-oriented activities. In universities, entrepreneurship education often includes coursework on entrepreneurship-related topics as well as opportunities to develop real ventures through funding, mentorship, and industry networking (Eesley and Wu, 2020; Souitaris et al., 2007; Von Graevenitz et al., 2010). Some universities even offer dedicated majors or minors in entrepreneurship[4]. Outside universities, entrepreneurship education is frequently delivered through incubators, accelerators, and founder training initiatives. These programs commonly provide cohort-based workshops, mentoring, peer communities, and structured guidance on venture operations, growth priorities, and external partnerships (Chatterji et al., 2019; Kotha et al., 2023; Lyons and Zhang, 2018). Across these settings, common program elements include classroom instruction, project-based work tied to real or simulated ventures, mentoring and advising, pitch or presentation milestones, and connections to entrepreneurial ecosystems (Eesley and Wu, 2020; Kotha et al., 2023; Lyons and

[4] https://www.usnews.com/best-colleges/rankings/business-entrepreneurship?myCollege=business&_sort=myCollege&_sortDirection=asc

Zhang, 2018; Peterman and Kennedy, 2003; Souitaris et al., 2007; Von Graevenitz et al., 2010).

As entrepreneurship education has become increasingly widespread, however, only a small body of research has comprehensively examined the effects of entrepreneurship training, and the evidence remains mixed. On the positive side, early studies report that, after completing entrepreneurship programs, participants self-report stronger perceptions of both the desirability and feasibility of entrepreneurship, as well as higher entrepreneurial intentions (Souitaris et al., 2007; Peterman and Kennedy, 2003). Later studies further develop this line of research to venture-level outcomes. Lyons and Zhang (2018) show that participants with less prior access to entrepreneurial opportunities benefit the most from such programs, as the training improves their entrepreneurial knowledge and expands their social networks. Camuffo et al. (2020) demonstrate that teaching nascent entrepreneurs a "scientific" approach to business-idea testing enables more efficient decision-making, allowing them to pivot effectively or abandon ventures before committing excessive resources. Chatterji et al. (2019) provide evidence that entrepreneurs can improve their people-management and organizational-design capabilities through targeted advice. Kotha et al. (2023) further find that structured entrepreneurship training helps early-growth entrepreneurs formulate innovation strategies, organize internal teams, and leverage external networks.

However, the findings are not uniform. Von Graevenitz et al. (2010) show that, although entrepreneurship education may enhance entrepreneurial self-efficacy and skills, it can actually reduce entrepreneurial intentions. Eesley and Lee (2021) find that university entrepreneurship programs do not necessarily increase entrepreneurship rates but instead improve the quality of entrepreneurial activity. Other scholars document outright negative effects: Bjorvatn et al. (2020) find that early exposure to entrepreneurship education does not encourage entry and may crowd out students' investment in formal schooling, especially when entrepreneurial activities are framed as an attractive alternative to academic achievement. Taken together, the evidence on the benefits of entrepreneurship education remains inconclusive, and important gaps persist in the existing literature. Prior research has primarily concentrated on entrepreneurial intentions or entry, leaving career outcomes largely unexplored. Even among studies that examine performance, the emphasis has been on venture-level outcomes such as survival, funding, or growth, rather than individual career trajectories. Since most ventures ultimately fail and many entrepreneurs eventually transition to traditional paid employment, it is important to understand how entrepreneurship education shapes students' career development outside entrepreneurship. Our study addresses this gap by examining the broader relationship between entrepreneurship education and non-entrepreneurial career outcomes.

II.B Entrepreneurship Education and Earnings Effects

Prior research suggests that entrepreneurial experience can have lasting effects on individuals' subsequent careers. Such experience may help individuals develop diverse and generalizable skills (Lazear, 2004; Campbell, 2013), while also revealing otherwise unobservable attributes, such as opportunity recognition, resource mobilization, and tolerance for risk and uncertainty (Shane, 2003; Gompers et al., 2005; Banalieva et al., 2018). A growing body of empirical work has examined how entrepreneurial experience affects subsequent labor market outcomes. While some studies find that such experience is associated with favorable career outcomes, others highlight more limited or even negative wage returns. For example, employees in California's semiconductor industry who joined start-ups earned more in the long run than comparable workers who remained in established firms (Campbell, 2013). Similarly, individuals who exited entrepreneurship and returned to paid employment have been shown to earn higher incomes, particularly when hired by highly innovative firms (Luzzi and Sasson, 2016). In contrast, other studies identify labor market penalties associated with prior entrepreneurship. Baptista et al. (2012) find that although former business owners tend to enter firms at higher hierarchical levels and experience faster promotions, their business ownership experience receives lower wage returns than comparable wage-employment experience. More recent evidence further suggests that former entrepreneurs may face persistent long-term earnings penalties (Mahieu et al., 2022).

One reason for these mixed findings is that entrepreneurial experience is difficult to separate from selection into entrepreneurship. Individuals who choose entrepreneurial careers may differ systematically from those who enter standard wage employment. Entrepreneurs often accept lower cash compensation than comparable employees in established firms (Hamilton, 2000), partly because entrepreneurship offers non-pecuniary benefits, including psychological rewards (Benz and Frey, 2008), greater autonomy and customized incentives (Zenger, 1992), and the possibility of large financial payoffs through liquidity events (Campbell, 2013). At the same time, entrepreneurial careers involve substantial risk and uncertainty, as entrepreneurial environments are volatile and unpredictable (Alvarez and Barney, 2005; Wu and Knott, 2006). These compensating differentials imply that individuals who enter entrepreneurship may already possess distinctive unobservable traits, such as higher risk tolerance, stronger intrinsic motivation, greater preference for autonomy, or lower attachment to conventional organizational careers. As a result, observed differences in later career outcomes may reflect not only the treatment effect of entrepreneurial experience, but also the characteristics of individuals who self-select into entrepreneurial roles. Moreover, entrepreneurship education may differ from entrepreneurial experience in how it is interpreted by employers and students themselves. On the demand side of the labor mar-

ket, employers may view former entrepreneurs as less committed to organizational authority and more oriented toward independence and autonomy (Hamilton, 2000; Moskowitz and Vissing-Jørgensen, 2002; Vissa, 2012; Kacperczyk and Younkin, 2022).

Studying university-based entrepreneurship education may help address these challenges for several reasons. First, compared with actual entrepreneurial entry or start-up employment, entrepreneurship education typically imposes lower entry barriers and does not require students to bear the same market-based trade-offs in income, risk, and career commitment. It therefore provides a useful setting for examining whether exposure to entrepreneurial knowledge, skills, and mindsets can shape subsequent career development while mitigating some of the selection concerns that complicate studies of real entrepreneurial experience. In addition, university-based entrepreneurship education may be interpreted differently from actual entrepreneurial experience in the labor market. Whereas former entrepreneurs may sometimes face concerns about their fit with wage employment, participation in entrepreneurship programs may signal initiative, business competence, and adaptability without necessarily raising doubts about commitment to organizational employment. Entrepreneurship education may also help students recalibrate overly optimistic expectations about entrepreneurship, better understand their own preferences and capabilities, and evaluate their fit with different career paths before entering the labor market (Baptista et al., 2012; Campbell, 2013; Luzzi and Sasson, 2016; Mahieu et al., 2022). Thus, university-based entrepreneurship education provides a useful context for examining how entrepreneurial exposure shapes subsequent wage-employment outcomes while reducing the selection concerns and potential labor market penalties associated with actual entrepreneurial experience.

II.C Hypothesis Development

In this section, we develop hypotheses on the relationship between entrepreneurship program participation and students' initial full-time job choices, distinguishing between self-employment and wage employment, and further examine job alignment among those who enter wage employment. Conventional wisdom suggests that entrepreneurship education should increase the likelihood that students pursue entrepreneurial careers by developing entrepreneurial ability and providing access to resources and networks (Lyons and Zhang, 2018; Rigby and Ramlogan, 2016). However, emerging research challenges this optimistic view. Some scholars posit that entrepreneurship is primarily rooted in inherent traits and predispositions (Nicolaou et al., 2008), rather than being fully cultivated through formal education. From this perspective, the primary function of entrepreneurship education is not to create entrepreneurs, but rather to help individuals better assess whether they possess the specific abilities and skills required for entrepreneurial activity. Prior research is broadly

consistent with this view, showing that entrepreneurship education can provide important signals about individuals' relative ability and the extent to which their skills match the demanding requirements of entrepreneurship (Lerner and Malmendier, 2013; Von Graevenitz et al., 2010). Such signals of entrepreneurial fit may correct students' initial overconfidence and improve their self-assessment, making them more aware of the gap between their current capabilities and those necessary for entrepreneurial success (Levine and Rubinstein, 2017; Eesley and Lee, 2021; Von Graevenitz et al., 2010). As a result, entrepreneurship education may have no impact on entrepreneurial entry or may even discourage it. Existing empirical evidence from both government-sponsored and school-based entrepreneurship education supports this "weeding-out" mechanism. For instance, a randomized controlled trial of a large-scale government entrepreneurship training program found no lasting effects on entrepreneurship rates or business performance (Fairlie et al., 2015). Similarly, Oosterbeek et al. (2010) find that a school-based entrepreneurship education program has no significant effect on students' self-assessed entrepreneurial skills and even exerts a negative effect on their willingness to become entrepreneurs. In addition, research on engineering school entrepreneurship programs suggests that such initiatives often have zero or even negative effects on actual entrepreneurial participation (Eesley and Lee, 2021). Accordingly, we hypothesize that graduates who participate in school-based entrepreneurship training may exhibit a lower likelihood of choosing self-employment as their first job.

Hypothesis 1 (H1): *Compared to nonparticipants, students who participate in entrepreneurship training may be less likely to choose self-employment as their first full-time job after completing the program.*

Next, we investigate how entrepreneurship education shapes participants' career choices, with a particular focus on their likelihood of entering wage employment and their career outcomes. We propose that individuals who participate in entrepreneurship education tend to achieve better job match quality in subsequent wage employment. This argument is anchored in the "jack-of-all-trades" perspective, which posits that entrepreneurs are generalists with a balanced portfolio of skills across multiple domains, rather than individuals with highly specialized human capital (Åstebro and Thompson, 2011; Lazear, 2004). Because start-ups are typically resource-constrained and have relatively small workforces (Aldrich, 1999; Rosen, 1983), individuals in such settings are often required to perform a wide range of tasks and assume substantial responsibility. Entrepreneurship education simulates these conditions by exposing students to multitasking, complex problem-solving, and high-level decision-making within a compressed time frame (Campbell, 2013; Dobrev and Barnett, 2005; Elfenbein et al., 2010). Such exposure broadens students' understanding of different functions, work demands, and professional roles. Building on the learning-about-comparative-advantage per-

spective, we argue that entrepreneurship education provides students with opportunities to engage in diverse tasks and responsibilities before entering the labor market. Such exposure helps them accumulate broad human capital, develop a clearer understanding of different types of work, and gain insight into their comparative advantages (Papageorgiou, 2014). As a result, they are better able to identify wage employment positions that align with their abilities and interests, thereby improving job match quality upon labor market entry.

Hypothesis 2 (H2): *Compared to nonparticipants, students who participate in entrepreneurship training may exhibit better alignment with their first full-time jobs after completing the program.*

III RESEARCH CONTEXT, DATA, AND MEASUREMENTS

III.A Research Context and Empirical Setting

An informative empirical setting for our research question should ideally satisfy two conditions. First, it should involve a well-developed entrepreneurship program that offers intensive and economically meaningful training. Second, it should permit a credible comparison between students who receive the training and otherwise similar students who do not. A simple comparison between participants and the broader student population may create potential selection bias, because students with stronger entrepreneurial ability or motivation may be more likely both to apply for such programs and to pursue distinctive career paths afterward (Card, 1999; Eesley and Lee, 2021). Our research setting is well suited to addressing this challenge, as the program provides intensive entrepreneurial training, while its selective admissions process enables us to construct a comparison group of applicants who expressed interest in the program but were not admitted. Specifically, we examine an entrepreneurial education initiative at a leading science and engineering university in the United States. Launched in 2014, the program has been offered annually for more than a decade. It aims to cultivate students' entrepreneurial confidence by providing opportunities to transform ideas into viable ventures. At its core is an accelerator that offers a structured pathway for students to develop and commercialize their projects while still enrolled.

The program is open to students at all levels, as well as to faculty, researchers, and alumni through affiliated tracks. Applicants may apply individually or in teams, provided that at least one co-founder is affiliated with the university. Each team submits an online application form and is invited for an interview. A selection committee then evaluates applicants and determines the number of teams admitted each year, subject to resource constraints. On average, approximately one-sixth of applicant teams are admitted to the program. This selective admissions process is central to our identification strategy. Following Lyons and Zhang (2018), we define the relevant counterfactual as applicants who sought

entry into the program but were not admitted and use these non-admitted applicants as the control group. Both admitted and non-admitted applicants demonstrated entrepreneurial interest by applying to the program; however, only admitted teams received exposure to the summer accelerator. Under this design, non-admitted applicants approximate the labor market outcomes that participants would have experienced had they not been admitted to the program.

Once admitted, participants join a 12-week, full-time summer accelerator where selected teams focus exclusively on developing their ventures. Structured as a zero-credit internship and formally recorded on students' transcripts, the program embodies the idea of "doing an internship for oneself." Upon acceptance, each team receives an initial seed grant of $4,000–$5,000, along with access to more than $200,000 in investment from an independently managed startup fund. Participants receive intensive mentorship throughout the program. Each team is assigned a dedicated coach, typically an experienced entrepreneur, early-stage operator, or alumni founder, who meets with them weekly to support the refinement of business models, validation of market assumptions, and strategic pivots. Students are also encouraged to engage with potential industry partners to identify and explore market opportunities before scaling. Through iterative learning and guided experimentation, the program enables participants to translate early-stage ideas into viable ventures while fostering an entrepreneurial mindset. The program culminates in Demo Day, a university-sponsored event where teams present their ventures to potential investors, industry partners, and the broader entrepreneurial community. This event serves as a key networking platform, facilitating connections among founders, investors, and business leaders. To date, the initiative has supported the creation of more than 560 startups, with a combined valuation exceeding $2.4 billion.

III.B Data Description

In this study, we draw on two novel data sources: (i) administrative records from the university entrepreneurship program and (ii) online résumé data from Revelio, which provide background information on individuals' educational and employment histories. The administrative records consist of two related datasets. The first is an application dataset that records individuals who applied to the program, including their names, school email addresses, and admission decisions. The second is a participation dataset that identifies individuals who ultimately participated in the program as startup founders. This dataset also contains detailed founder background information, including unique identifiers (Founder ID), names, locations, cohort years, LinkedIn URLs, and school email addresses. Overall, the application dataset includes 1,536 applicants through 2023, of whom 340 were admitted to the program

and 1,196 were not admitted. By comparison, the participation dataset records 1,241 unique individuals who enrolled in the program by 2023. Several factors explain the discrepancy between the two datasets. First, some information is missing because of limitations in the record-keeping process. Second, startup team composition may change after the application stage, as founders can be added or removed. In addition, follow-up emails used to collect applicant information are sent to team members after teams submit their applications, but not all applicants respond. As a result, the application records do not fully capture the final set of individuals associated with each application. Figure 1 shows the number of participants and recorded applicants in the program over time and indicates a steady increase in both groups across cohorts.

We use Revelio Labs' résumé profile dataset to track individuals' employment and educational backgrounds. This dataset, which has been widely used to study career development trajectories (Tambe and Hitt, 2014; Forderer and Burtch, 2025), contains individual demographic information such as gender and ethnicity, as well as detailed work histories, including start and end dates of employment, job titles, locations, job categories, job classifications (O*NET codes), and estimated salaries. It also includes educational records such as schools attended, degrees earned, and graduation dates. As is typical in résumés, individuals create separate entries for each job position, even within the same firm. This structure allows us to observe career trajectories and salary changes both within and across firms and positions. The dataset is right-censored as of April 1, 2024.

We identify individuals from program records and match them to profiles in the Revelio database using names, LinkedIn URLs, and educational backgrounds. This matching process yields 919 participants. Our analysis focuses exclusively on *full-time employment* reported on individuals' résumés[5] that began after program completion. For program participants, this refers to August of the cohort year in which they participated in the program; for the control group, it refers to August of the cohort year corresponding to their application. This restriction ensures that all observed labor market outcomes occur after the relevant treatment or assignment point. In addition, because our main analysis centers on early career outcomes, we place particular emphasis on the *first full-time job* observed after program application. The final treatment sample consists of 415 individuals with at least one full-time job beginning after their application to the program. We also match 821 applicants who were not admitted to the program to the Revelio database. Applying the same sample restrictions, the control sample includes 533 individuals with at least one full-time job beginning after

[5]We identify likely full-time employment based on job titles reported on online résumés. Positions explicitly labeled as internships, co-op positions, part-time roles, on-campus activities, academic research positions, student projects associated with the entrepreneurship program, and other clearly non-full-time positions are excluded from the analysis.

their application.

III.C Measurements

III.C.1 Self-Employment versus Wage Employment

First, we examine whether individuals who participate in entrepreneurship education programs differ from nonparticipants in their initial job choices, focusing on whether their first full-time position is in self-employment or wage employment. Individuals' employment status is identified based on the job titles listed on their online résumés. To capture these outcomes, we distinguish between two employment statuses. (i) *Self-employment*: individuals who are self-employed in either an unincorporated business, such as a proprietorship or partnership in which they actively work, or an incorporated business in which they hold an ownership position and actively work (Folta et al., 2010; Levine and Rubinstein, 2017). (ii) *Wage employment*: individuals whose first job is a paid employee position in an organization in which they do not hold an ownership stake. To be classified as holding pure wage employment, an individual must have no self-employment involvement during the first employment spell.

III.C.2 Career Progression and Match Quality

Next, we focus on individuals whose first employment status is classified as wage employment or hybrid employment and assess the quality of the worker–job match based on subsequent career progression. Prior research suggests that higher wage growth (Jackson, 2013) and lower job separation are associated with better job matches (Jovanovic, 1984; Fredriksson et al., 2018). Accordingly, we measure match quality using two proxies: compensation and career transitions in the first full-time job. Compensation is measured using estimated annual salary, denoted as *Salary*, inferred from Revelio Labs data. Revelio generates salary estimates using a predictive model that incorporates position-specific attributes (e.g., job title, company, location, and industry), worker-specific attributes (such as tenure at the firm), and the year of observation. The model is trained on multiple data sources, including publicly available visa applications, self-reported salaries, and job postings[6]. This salary measure has been used in several published articles (Docimo and Xu, 2026; Liang et al., 2025; Marchetti and Puranam, 2026) and working papers (Amanzadeh et al., 2024; Gao et al., 2023; Guenzel et al., 2026; Hampole et al., 2025; He et al., 2024). We interpret higher estimated salaries as indicative of better job matches, as they reflect the market value of the worker–job pairing.

[6]We also use salary data reported on Glassdoor as an alternative compensation measure to validate our findings and further assess the robustness of our results, as shown in Section 6.4.

In addition, we trace individuals' employment histories using their résumé profiles to identify career transitions, distinguishing between two types: current employer tenure and current occupation tenure. Current employer tenure is a time-to-event outcome, defined as the duration of an individual's employment spell with the current employer, ending when the individual begins a new employment spell with a different employer, enters self-employment, or exits employment altogether. Consistent with Fredriksson et al. (2018), longer tenure with the current employer and a higher likelihood of remaining with the current employer are associated with better worker-employer matches. We also examine time to promotion as a competing time-to-event outcome, defined as the duration from the start of the first job to a within-firm position change accompanied by an increase in estimated salary. Furthermore, to capture underlying individual-occupation match, we follow Neal (1999), who distinguishes between employer matches and occupational matches. In this framework, workers search not only for a suitable employer but also for an occupational path that best fits their skills. As workers accumulate experience and learn about their comparative advantages, occupational switching becomes less frequent. Motivated by this insight, we construct an alternative measure of tenure within the current occupational category, defined as the duration from the start of the job spell to an occupational switch. An occupational switch is identified when the first two digits of an individual's O*NET occupation code change across different positions.

III.C.3 Treatment

Program Participation equals one if the individual enrolled in the entrepreneurship training program and completed it by launching a startup, and zero otherwise.

III.C.4 Control Variables

We control for a set of individual characteristics, including demographic, educational, and pre-application work-experience variables. Demographic characteristics from Revelio include an indicator for whether the individual is female (*Female*) and an indicator for whether the individual's ethnicity is classified as a minority (non-White) (*Minority Indicator*). Educational variables capture attainment and credentials beyond the master's level, including MBA and doctoral degrees (*Advanced Degree Indicator*). We further measure pre-program industry experience using indicators for prior entrepreneurship experience (*Prior Self-Employment Experience Indicator*) and prior industry exposure (*Prior Industry Exposure Indicator*). These are defined, respectively, as binary variables indicating whether the individual had ever been

self-employed or had any wage-employment experience[7] as of April of the cohort year in which the individual applied to the program. Finally, we measure *Number of Prior Positions* as the number of distinct positions an applicant held before applying, including self-employment, to capture the breadth of their prior industry exposure.

Tables 1–2 present the summary statistics for the main variables used in the analysis among applicants with post-program employment records. As shown in Table 1, 43.8% of the sample participated in the program. About 18.6% of the sample had prior self-employment experience, while roughly 80.3% had some form of prior industry exposure before entering the program. On average, individuals in the sample had worked in 2.01 distinct positions. The demographic characteristics show that about 45.7% of applicants held a master's degree or higher, 23.0% were female, and 52.5% were from minority ethnic groups. Turning to post-program career outcomes, approximately 9.1% of applicants entered self-employment as their first post-program full-time job. Among those whose first full-time post-program job was wage employment, the average log annual salary was 11.53, with a standard deviation of 0.493. Salary is measured in annual U.S. dollars before taking the logarithm. Figure 2 shows the distribution of log annual salary.

Table 2 reports descriptive statistics for employer and occupational transitions among participants and controls. Within the observation window, 28.86% of participants experienced an employer switch, with an average tenure of 2.46 half-years, while 13.67% experienced a promotion, with an average tenure of 2.84 half-years. Among controls, 34.03% experienced an employer switch, with an average tenure of 2.18 half-years, while 20.17% experienced a promotion, with an average tenure of 2.86 half-years. The censored share was 57.64% among participants and 45.80% among controls in the employer-transition sample. For occupational transitions, 21.32% of participants experienced an occupational switch, with an average tenure of 3.74 half-years, while 78.67% were censored. Among controls, 30.80% experienced an occupational switch, with an average tenure of 3.88 half-years, while 69.20% were censored. Overall, controls exhibit higher rates of employer transitions, promotions, and occupational transitions than participants during the observation window. The Kaplan–Meier survivor curve of career transition is presented in Figure 3.

IV MODEL SPECIFICATION

We estimate the following baseline specification to examine the relationship between entrepreneurship education and career outcomes:

[7]This includes full-time work, internships, co-op positions, and part-time roles, but excludes on-campus activities and academic research positions.

$$Y_i = \alpha + \beta_1 \text{Program Participation}_i + \theta C_i + \delta \text{Cohort Year}_i + \psi + \epsilon_i \quad (1)$$

where Y_i measures individual i's career outcome. Program Participation$_i$ indicates whether individual i participated in the program. C_i is a vector of individual-level covariates, and Cohort Year$_i$ denotes cohort-year fixed effects capturing common time-varying factors within each applicant cohort. For the control group, the cohort year is defined as the year in which the individual applied to the program. Standard errors are clustered at the individual level.

We begin by comparing program participants with the control group in their initial job choices, focusing on the likelihood of selecting self-employment over wage employment, estimated using a logit model. We then examine early career outcomes by estimating OLS models with compensation in the first full-time position as the dependent variable. For career transitions, we instead employ survival analysis. OLS regression is not appropriate because it excludes individuals whose employment status has not yet changed and cannot account for alternative outcomes that become unobservable once one outcome occurs, whereas duration models address these issues. Therefore, we adopt an accelerated failure time (AFT) model based on Harhoff and Wagner (2009), with a Weibull distribution[8]. The model is specified as $\ln T_i = X_i\beta + \epsilon_i$, where $X_i\beta$ corresponds to the linear specification in Equation (1), and the error term ϵ_i follows an extreme value distribution. This specification allows coefficients to be interpreted directly in terms of acceleration or deceleration of the time to failure. Negative coefficients ($\beta < 0$) indicate a shorter expected duration (i.e., faster career progression), whereas positive coefficients imply a longer time to transition. An advantage of AFT models is that coefficients can be interpreted directly as changes in duration, whereas Cox PH coefficients reflect relative risks of exit within a given time interval[9]. In the current-employer tenure analysis, the dependent variable is tenure with the initial employer, which is measured in half-years, and promotion is treated as a competing outcome. To account for this possibility, we estimate competing-risks models that allow for destination-specific effects by treating alternative exits as right-censored at the time they occur (Cox et al., 1984). In the occupational-tenure analysis, the dependent variable is tenure in the initial occupation, also measured in half-years.

[8]Unlike the semi-parametric Cox proportional hazards (PH) model, which does not assume a specific functional form for the survival distribution, AFT models rely on parametric assumptions about the survival and hazard functions. Our findings are robust to estimating AFT models under alternative distributional assumptions, including log-normal, log-logistic, and exponential specifications.

[9]We also estimate Cox proportional hazards models as a robustness check and obtain similar results.

V RESULTS AND ANALYSIS

V.A Entry into Entrepreneurship

We first compare program participants with a control group to assess the prevalence of entrepreneurship relative to wage employment. Table 3 reports the coefficients from a logit model estimating differences in initial employment status between program participants and non-admitted applicants. The results indicate a negative, though statistically insignificant, difference ($p = 0.693$) between participants and the control group in the likelihood of entering self-employment as an initial career path. This pattern is broadly consistent with the mechanism underlying Hypothesis 1: entrepreneurship education may help individuals better assess their fit for entrepreneurship, rather than necessarily increasing their likelihood of starting a venture. When the comparison is restricted to the pool of applicants, thereby conditioning on individuals who had already expressed interest in the program and were likely to have stronger latent entrepreneurial motivation, the differences remain statistically insignificant.

V.B Career Progression Analysis

We next examine how career progression differs between program participants and nonparticipants, beginning with wage outcomes as an indicator of job-match quality. If program participants obtain better job matches, they should earn higher wages in their first jobs. Table 4 suggests that, relative to non-admitted applicants, program participants earn approximately 8.27% higher salaries in their initial job placements, a significant difference at the 5% level ($p=0.014$). Given that the average annual salary in our sample is \$113.2k, this implies an earnings increase of roughly \$9.36k per year for program participants in their first job. Since each team receives initial seed funding of at most \$5k through the program, the estimated first-year wage gain alone exceeds the program's initial funding cost per team by at least \$4.36k. This comparison suggests that the program may generate economic returns even in the short run. Importantly, this calculation considers only the first-job salary gain for a single individual on the team and excludes any longer-term wage growth. Since the seed funding may support multiple team members rather than a single participant, the aggregate wage gains at the team level could be substantially larger. Therefore, this estimate likely represents a conservative lower bound on the program's value.

In addition to compensation, we examine how career transition patterns differ between program participants and nonparticipants. Table 5 reports estimates of the association between program participation and the timing of individuals' first transition from their initial full-time jobs. The estimate in Column (1) suggests that program participation is associated with 26.8% longer tenure with the initial employer ($p=0.099$), equivalent to an average

increase of 3.62 months. This finding is consistent with the salary results, suggesting that program participation may be associated with better initial job matching and greater stability in the first job. However, the estimate in Column (2) indicates that program participation is also associated with 33.3% longer duration until first promotion (p=0.051). One possible explanation is that participants obtain better-matched and higher-paying initial jobs and experience greater job satisfaction, which reduces the need for early internal mobility. In addition, our relatively short observation window may limit our ability to capture later promotion dynamics.

Furthermore, we estimate our baseline model using occupational change as an alternative measure of job alignment. The results, shown in Table 6, indicate that program participants exhibit 34.7% longer tenure in their initial occupation than non-admitted applicants in the control group (p=0.029), which is equivalent to approximately three additional months. This finding is consistent with the results from the compensation and employer-tenure analyses. Overall, our analysis shows that program participants have significantly higher compensation and longer tenure with both their first employer and their initial occupation in their first full-time jobs, relative to non-admitted applicants in our sample. Together, these results provide empirical evidence in support of H2, suggesting that program participants achieve higher job-match quality in their first full-time job placements.

V.C Salary Premiums by Prior Industry Exposure

In this section, we examine whether the effects of entrepreneurship education on non-entrepreneurial career outcomes vary with students' pre-program industry exposure. Students may enter entrepreneurship programs with different levels of industry knowledge, professional networks, and familiarity with workplace practices, making the extent to which they benefit from such education theoretically ambiguous. On the one hand, students with limited prior industry exposure may benefit more if entrepreneurship education compensates for their lack of preexisting industry knowledge by developing general human capital, expanding access to resources and networks, and providing early exposure to workplace-relevant skills and entrepreneurial capabilities (Campbell, 2013; Eesley and Wu, 2020; Lyons and Zhang, 2018). On the other hand, students with greater prior industry exposure and knowledge may be better able to absorb and apply entrepreneurial knowledge, identify and evaluate opportunities more effectively, and translate these skills into workplace settings (Cohen and Levinthal, 1990; Shane, 2000). As a result, they may make more informed career choices and achieve better job quality and higher salaries in their first post-program jobs.

As described in Section 3, we measure the breadth of students' pre-program industry exposure using the number of distinct prior employers, including both wage employment and

self-employment, and then examine heterogeneity in the relationship between entrepreneurship education and subsequent wage-employment outcomes by interacting program participation with the number of prior positions. Table 7 reports the results. Program participation remains positively and significantly associated with first full-time job salary. The coefficient on program participation remains statistically significant (p=0.014). However, the coefficient on the number of prior positions is negative, though statistically insignificant (p=0.392). One possible explanation is that, in a student sample, prior off-campus experience may not translate into wage gains in the same way as formal labor-market experience. Internships, co-op positions, and other short-term work experiences can vary substantially in quality, industry, and job content; therefore, greater diversity in prior employers does not necessarily imply the accumulation of higher-quality or more wage-relevant human capital. More importantly, the interaction between program participation and the number of prior positions is positive and marginally significant (p=0.061). This suggests that the wage premium associated with entrepreneurship education is larger for students with broader prior industry exposure. Specifically, among students with one additional prior position relative to the sample mean, program participation is associated with approximately 12.9% higher first-job earnings after the program. This pattern is consistent with the idea that students with broader pre-program industry exposure may be better able to absorb, contextualize, and apply the knowledge and skills gained from entrepreneurship education, thereby achieving better labor-market outcomes in their first post-program jobs.

VI ROBUSTNESS CHECK

VI.A Selection on Individual Characteristics

A potential concern in our baseline analysis is selection: although we restrict our analysis to finalists who completed the final stages of the application process and who therefore likely share relatively strong entrepreneurial motivation, these individuals may still differ in whether they ultimately participate in the program. Such differences may, in turn, affect subsequent career outcomes and career choices. To address this concern, we first examine whether students' pre-application characteristics predict admission to the entrepreneurship education program. This analysis helps assess whether the estimated treatment effect reflects selection on observable characteristics rather than the causal effect of program participation. The predictors used in this test are the same control variables included in the baseline specification, including students' demographic characteristics, prior industry experience, and previous entrepreneurial experience. These variables are included because prior research suggests that prior employment and entrepreneurial experience are relevant to individuals' entrepreneurial ability (Lazear, 2004). As reported in Table 8, most of the

estimated coefficients are small in magnitude and statistically insignificant. The only statistically significant predictor is whether the applicant held an advanced degree before entering the program. However, this pattern does not undermine our baseline findings. In the baseline model, having an advanced degree is positively and significantly associated with wages in the first employment spell. It is also positively associated with longer employer tenure and occupational tenure, although these coefficients are not statistically significant. Even if degree status affected selection into the program, the resulting selection pattern would likely work against finding a positive wage premium for program participants, since applicants without advanced degrees would be more likely to enter the program and would be expected to have lower subsequent earnings in their first job. The persistence of a positive program coefficient after controlling for this characteristic therefore suggests that the higher wages of participants are unlikely to be driven by this observable source of selection.

VI.B Coarsened Exact Matching

As a further check, we match the treatment and control groups so that the comparison is made among individuals with more similar pre-treatment characteristics. Although we restrict our analysis to finalists who completed the final stages of the application process and who therefore likely share relatively strong entrepreneurial motivation, these individuals may still differ in whether they ultimately participate in the program. Such differences may, in turn, affect subsequent career outcomes and career choices.

Furthermore, we employ coarsened exact matching (CEM) and one-to-one nearest-neighbor propensity score matching (PSM) with a logistic propensity score model as robustness checks. We then estimate the effect of program participation on the outcome in the matched sample using the corresponding matching weights. Specifically, we match accepted and non-admitted finalists on gender, ethnicity, advanced degree status, prior self-employment experience, prior industry exposure, and the number of prior positions held before applying to the program[10]. This procedure improves comparability between the treatment and control groups by restricting the analysis to observationally similar finalists while retaining a sufficiently large sample. Matching on these characteristics improves covariate balance and helps reduce concerns that the estimated effects are driven by preexisting differences rather than program participation. The results of this analysis are presented in Tables 9–13. Overall, the estimated associations between program participation, entrepreneurial activity, and the three measures of career transition remain similar in both magnitude and statistical significance to the baseline results.

[10]We do not include cohort year in the matching, as doing so would lead to a very small sample size.

VI.C Double Machine Learning Estimates

Although the matching analyses address observable covariate imbalance, they still require researcher discretion in selecting the covariates used for adjustment and specifying the functional form of the outcome model. We therefore examine whether the wage results are robust to a more flexible approach that models the relationships among covariates, treatment assignment, and outcomes. Specifically, we re-estimate the treatment effect within a double machine learning (DML) framework (Chernozhukov et al., 2018; Shi et al., 2025). This approach combines flexible machine-learning estimation of the nuisance functions with Neyman-orthogonal moment conditions and cross-fitting, allowing valid inference while relaxing functional-form assumptions. We estimate the average treatment effect of program participation on log starting wages using a doubly robust regression model, in which both the outcome regression and the propensity score are estimated by machine learning and combined so that the estimator remains consistent if either nuisance function is correctly specified (Robins and Rotnitzky, 1995). We estimate the nuisance functions using three distinct methods: (i) L1-penalized regressions (LASSO and logistic LASSO) applied to a high-dimensional set of covariates and their pairwise interactions; (ii) random forests; and (iii) XGBoost. In our setting, the candidate controls include the covariates used above in the matching analysis, together with the duration of prior industry exposure before application, field-of-study fixed effects, and cohort fixed effects, yielding a total of 67 controls. For the LASSO, we further add all pairwise interactions, producing 613 high-dimensional controls from which the LASSO selects a sparse subset. The random forest and XGBoost learners are given the 67 controls directly. As shown in Table 14, the DML estimates are stable across methods and consistent with the baseline OLS estimates: program participation is associated with an increase in starting wages of approximately 7.3% under the LASSO, 9.1% under random forests, and 8.4% under XGBoost, each statistically significant at the 5% level.

VI.D Instrumental Variable Analysis

The preceding analyses reduce concerns about observable selection and model dependence, but they cannot fully rule out selection on unobserved characteristics. We therefore introduce an instrumental-variable analysis as an additional check on whether the positive wage results persist under a different source of identifying variation. We are interested in identifying the causal impact of the entrepreneurship program on participants' subsequent career trajectories. The matching and double machine learning analyses provide evidence that our results are not driven solely by differences in observable characteristics between participants and nonparticipants. However, these approaches still rely on the assumption that selection into

the program is fully captured by observed covariates. This assumption may be strong in our setting, as individuals who apply to and are selected into entrepreneurship-related classes and programs may differ from others in unobserved dimensions. These unobserved factors could also shape subsequent career progression, raising concerns about remaining omitted-variable bias. To further address this concern, we implement an instrumental-variable strategy. We introduce a novel instrument based on the log-transformed number of prior program participants who entered the university in the same admission year as the focal individual. In other words, for each individual, the instrument captures how many earlier program participants belonged to the same university admission cohort. Individuals whose admission cohorts include more prior program participants are more likely to know peers who have taken part in the entrepreneurship program. These peers may provide information about the program and reduce uncertainty about applying to and participating in it. Prior research shows that peer influence can promote entrepreneurial entry by shaping motivation, transmitting opportunity-related information, and reducing uncertainty (Kacperczyk, 2013; Nanda and Sørensen, 2010). Related research also suggests that peer effects may shape participation in social programs through the diffusion of information about program benefits and costs (Dahl et al., 2014). Accordingly, the log number of prior program participants from the same university admission cohort is likely to influence the focal individual's likelihood of entrepreneurship program participation. At the same time, this measure should not directly affect later career outcomes beyond self-employment except through program participation. Prior research uses program exposure to coworkers as an instrument for individual participation (Duflo and Saez, 2003). To construct this instrument, we focus on students and alumni with education records. We first obtain individuals' admission years from the university administrative database, provided by the University's Office of Enrollment. When an individual cannot be identified in the administrative records, we supplement the admission-year information using the self-reported start year of university education from the individual's online résumé. We exclude individuals whose online résumés do not report any university education experience. We also exclude the program's 2014 cohort from this analysis. We then estimate the following two-stage least squares specification. In the first stage, we regress program participation on the instrument and the same set of control variables used in Equation (1):

$$\text{Program Participation}_i = \alpha + \beta_1 IV_i + \theta C_i + \delta \text{Cohort Year}_i + \psi + \nu_i, \tag{2}$$

where IV_i denotes the log number of prior program participants who entered the university in the same admission year as individual i. In the second stage, we estimate Equation (1) using the predicted value of program participation from the first stage:

$$Y_i = \alpha + \pi_1 \widehat{\text{Program Participation}}_i + \theta C_i + \delta \text{Cohort Year}_i + \psi + \epsilon_i. \quad (3)$$

Here, $\widehat{\text{Program Participation}}_i$ is the predicted value of program participation obtained from the first-stage regression. In this analysis, Y_i represents the annual salary in the first full-time job. The coefficient π_1 captures the 2SLS estimate of the effect of program participation on later earnings. As shown in Table 15, participation in the entrepreneurship program increases annual salary in the first full-time job by approximately 35%, which is directionally consistent with the OLS estimates. The first-stage F-statistic is 32.9, suggesting a strong relationship between the instrument and program participation.

VI.E Alternative Compensation Data

We next turn from identification concerns to measurement concerns. Because the baseline wage results rely on compensation estimates from Revelio Labs, we examine whether the findings are robust to an alternative salary measure constructed from a separate data source. In addition to the compensation estimates from Revelio Labs, we construct an alternative measure of compensation using median total pay reported on Glassdoor. Glassdoor salary data consist of self-reported compensation records submitted by employees and job seekers and have been used in several published studies (Babenko and Sen, 2014; Forderer and Burtch, 2025; Hampole et al., 2026; Li, 2025). We infer expected compensation from applicants' online résumé profiles using information on firm, job title, and geographic location. This procedure allows us to match 61% of the applicant sample to Glassdoor salary records. In the matched Glassdoor data, the mean log annual salary is 11.86, with a standard deviation of 0.42. Using this alternative measure, we show in Table A.1 that our results are robust: the coefficient magnitudes and statistical significance are similar to those in the baseline specification. In particular, compared with applicants whose applications were not accepted, accepted applicants earn approximately 7.73% higher wages in their first post-application wage-employment spell.

VI.F Sensitivity Check

Beyond the main wage specification, the analysis also relies on several modeling and sample-construction choices for the career-transition outcomes. We therefore conduct additional sensitivity analyses to assess whether the conclusions change under alternative duration models, sample restrictions, outlier treatments, and occupational controls. The results are reported in the Online Appendix. First, we assess the robustness of our career-transition results to alternative model specifications. In addition to the Weibull AFT models used in the baseline analysis, we estimate Cox proportional hazards models, in which coefficients are in-

terpreted as semi-elasticities of the hazard rate. The results are reported in Tables A.2–A.3. Table A.2 examines the relationship between program participation and career transitions involving the initial employer. The estimate in Column (1) indicates that program participation is associated with a 20.1% lower hazard of exiting the initial employer (p=0.098). This implies that, conditional on remaining in the initial job up to a given point in time, program participants tend to stay with their initial employer longer than nonparticipants. Column (2) shows that program participation is also associated with a significantly lower hazard of internal advancement (p=0.048), consistent with the baseline AFT results. Table A.3 reports the Cox model estimates for the first occupational transition. The results show a significantly lower hazard of switching out of the initial occupation among program participants (p=0.029), which is also consistent with the baseline finding that participants remain longer in their initial occupation type and are slower to change occupations. Overall, these results support the interpretation that program participants may experience better initial job matches.

Second, we examine whether our findings are driven by individuals with repeated program participation. Across all participant records, 2.1% of participants have multiple program participation records. After excluding these individuals and re-estimating the models, the results remain directionally and statistically similar to the baseline estimates (Tables A.4–A.7), except that the estimate for tenure with the current employer is marginally insignificant (p = 0.156). Third, in the salary analysis, we assess the sensitivity of our estimates to the presence of extreme values. Specifically, we trim the treatment and control groups separately by removing observations at the 1st and 99th percentiles, the 5th and 95th percentiles, and the 10th and 90th percentiles of the salary distribution. Across all trimming specifications, the estimated effects remain similar in magnitude and statistical significance (Table A.8). Overall, these sensitivity analyses suggest that our results are robust to alternative model specifications, sample restrictions, and the treatment of outliers.

Third, we add dummy variables for occupational groups, defined using the first two digits of the O*NET code, and rerun the career transition analysis of tenure with the initial employer, because career mobility may vary across occupations (Huang and Zhang, 2016). The results are consistent with the baseline estimates, as shown in Table A.9. We do not include these variables in the wage analysis because program participation may itself affect entry into a particular occupational category. In other words, the program may open pathways into specific industries or occupations. Following Angrist and Pischke (2009), controlling for variables that are themselves potential outcomes of the treatment–often referred to as "bad controls"–can induce selection bias and obscure the program's total effect on wages. For the same reason, we do not conduct the corresponding analysis for tenure within the initial

occupation, because tenure in the initial occupation may be highly correlated with current occupational categories. Thus, we restrict the inclusion of these additional controls to the tenure-with-initial-employer analysis.

VI.G Sampling Bias

Finally, we examine whether the construction of the application-linked sample could affect the interpretation of the results. This check is important because some program participants cannot be linked to the application records, and any systematic differences between linked and unlinked participants could limit the representativeness of the analysis sample. As discussed in Section 3.2, the application records do not fully capture the final set of individuals. To assess the potential bias of the application subsample, we compare observable characteristics between the full sample of program participants and the subset of participants who are also reported in the application records. Among the 919 program participants in the full sample, 261 individuals can be linked to the application data. This comparison allows us to evaluate whether the linked subsample differs meaningfully from the broader participant population. As reported in Table A.10, the results suggest that the linked subsample is broadly similar to the full participant sample across most observed characteristics. The only statistically significant difference is prior self-employment experience: individuals reported in the application records are more likely to have prior self-employment experience than participants in the full sample. Other characteristics, including prior work experience, the Number of Prior Positions, advanced degree status, gender, and minority status, do not differ significantly between the two groups.

VII DISCUSSION

This study provides new evidence on how university-based entrepreneurship programs influence students' long-term career development beyond new venture creation. Using matched data that combine program participation and application records with detailed online résumé profiles, we examine the labor market outcomes of program participants relative to comparable peers whose applications were not accepted. Our findings show that participation does not significantly increase the likelihood of self-employment in the first job after program completion. However, among graduates who initially enter wage employment, program participants exhibit better job matches and stronger labor-market outcomes. Specifically, participants are less likely to make early career transitions, suggesting better initial job alignment. They also achieve higher estimated salaries, indicating superior labor-market performance.

Our study makes two theoretical contributions. First, we contribute to the ongoing

debate on the value of university entrepreneurship programs. Prior research has shown that such programs may have limited or no lasting effects on entrepreneurship rates or venture performance (Fairlie et al., 2015). Building on this perspective, our study examines the other side of the coin by asking whether entrepreneurship education may generate sustained benefits beyond venture outcomes. In particular, we show that students may benefit from entrepreneurship programs even when they do not become entrepreneurs, as the training appears to improve their subsequent fit into career roles and performance in the broader labor market. In doing so, our study responds to calls to better understand the broader career consequences of university entrepreneurship education (Eesley and Lee, 2021).

Second, we extend the literature on entrepreneurial experience and subsequent career outcomes. Prior research has examined how real-life entrepreneurial experience affects future earnings and employment trajectories, but such evidence is often complicated by selection concerns. Individuals who enter start-ups or entrepreneurship may differ systematically in risk tolerance, intrinsic motivation, and preferences for non-pecuniary rewards. As a result, observed career outcomes may reflect both entrepreneurial experience and preexisting individual traits. We mitigate this concern by focusing on university-based entrepreneurship training, a lower-stakes and more inclusive setting that exposes students to entrepreneurial learning without requiring actual entry into entrepreneurship. This allows us to better isolate how entrepreneurial education itself shapes later career progression. Our findings also stand in contrast to prior studies showing that individuals who transition from entrepreneurship back to wage employment often experience an earnings penalty (Campbell, 2013; Mahieu et al., 2022). Our unique dataset allows us to study students' exposure to entrepreneurship education before their entry into the labor market. The positive salary and job-match effects we document suggest that entrepreneurial learning can enhance career outcomes even outside entrepreneurship.

Our findings have several practical implications for universities, students, and employers. First, for universities and program administrators, the results suggest that entrepreneurship education should not be evaluated solely by start-up creation or immediate self-employment rates, as such programs may also improve outcomes among students who enter wage employment. This implies that the value of entrepreneurship programs is broader than venture formation. Universities should therefore adopt a more comprehensive evaluation framework that includes job match, salary growth, career stability, and performance in traditional employment settings.

Second, for students, our findings indicate that entrepreneurship education can be valuable even for those who do not plan to become entrepreneurs immediately. Participation in such programs may help students better understand their skills, preferences, and career

opportunities, enabling them to make better first-job choices. The combination of higher salaries and lower early mobility suggests that participants are more likely to find jobs that fit their capabilities and career goals. Students should therefore view entrepreneurship programs not only as preparation for founding a start-up, but also as training that can improve outcomes in broader career paths, including employment in established firms.

Third, for companies, entrepreneurship program participants may represent a valuable pool of talent. Their lower early career mobility suggests stronger job fit and potentially higher retention. Their higher compensation also implies that employers may recognize and reward the practical skills developed through entrepreneurship training, such as opportunity recognition, problem solving, initiative, adaptability, and cross-functional thinking.

Overall, this study suggests that university entrepreneurship programs create value not only by encouraging and supporting new venture creation, but also by improving students' broader labor-market outcomes. Entrepreneurship education can function as a form of career preparation that enhances job matching, compensation, and early career stability, especially for students who pursue wage employment after graduation.

This study has several limitations that point to opportunities for future research. First, our analysis is based on data from a single university-based entrepreneurship program. Although this setting provides rich longitudinal information on applicants and participants, future research could examine similar programs across multiple institutions to assess the generalizability of our findings across different educational contexts, student populations, and program designs. Second, our analysis does not rely on directly observed salary records. Instead, earnings-related outcomes are estimated from résumé-based career histories and external labor-market information. Future work could link entrepreneurship education records to administrative earnings data or employer-reported compensation records to provide more precise estimates of the labor-market returns associated with entrepreneurship education.

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TABLES

Table 1: Summary Statistics

Variables	Obs.	Mean	Std. Dev.	Min	Max
Career Outcomes					
First Post-Program Self-Employment	948	0.091	0.287	0	1
Log Annual Salary	858	11.532	0.493	8.886	13.163
Characteristics					
Program Participation	948	0.438	0.496	0	1
Prior Self-Employment Experience Indicator	948	0.186	0.389	0	1
Prior Industry Exposure Indicator	948	0.803	0.398	0	1
Number of Prior Positions	948	2.006	1.717	0	11
Advanced Degree Indicator	948	0.457	0.498	0	1
Female Indicator	948	0.230	0.421	0	1
Minority Indicator	948	0.525	0.500	0	1

Table 2: Average Time to Career Transition

Group	Observations	Initial Employer		Promotion		Censored
		Share (%)	Tenure (Half Years)	Share (%)	Tenure (Half Years)	Share (%)
Employer Transition						
Participants	376	28.86	2.46	13.67	2.84	57.64
Controls	473	34.03	2.18	20.17	2.86	45.80
Occupational Transition						
Group	**Observations**	**Initial Occupation**				**Censored**
		Share (%)	**Tenure (Half Years)**			**Share (%)**
Participants	347	21.32	3.74			78.67
Controls	448	30.80	3.88			69.20

Table 3: Logistic Regression Estimates for First Full-Time Job Outcomes

Variables	First Full-Time Job
Program Participation	-0.0967
	(0.245)
Prior Self-Employment Experience Indicator	0.412
	(0.308)
Prior Industry Exposure Indicator	0.0361
	(0.366)
Number of Prior Positions	-0.0341
	(0.0949)
Advanced Degree Indicator	-0.333
	(0.243)
Female Indicator	-0.504
	(0.317)
Minority Indicator	0.489**
	(0.239)
Cohort Dummies	Yes
Observations	948
Wald χ^2	32.65
Log Likelihood	-275.193

Notes. Robust standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4: OLS Estimates for Compensation in First Full-Time Job

Variables	Log Annual Salary
Program Participation	0.0827**
	(0.0337)
Prior Self-Employment Experience Indicator	-0.0255
	(0.0542)
Prior Industry Exposure Indicator	0.00747
	(0.0512)
Number of Prior Positions	0.00123
	(0.0180)
Advanced Degree Indicator	0.119***
	(0.0321)
Female Indicator	−0.119***
	(0.0430)
Minority Indicator	0.00388
	(0.0327)
Cohort Dummies	Yes
Observations	858
R-squared	0.0674

Notes. The sample includes individuals whose first job is wage employment. Robust standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: AFT Estimates of Tenure with Initial Employer

Variables	Tenure with Initial Employer	Tenure to Promotion
Program Participation	0.237*	0.288*
	(0.144)	(0.148)
Prior Self-Employment Experience Indicator	-0.245	-0.0631
	(0.207)	(0.216)
Prior Industry Exposure Indicator	0.129	0.241
	(0.205)	(0.226)
Number of Prior Positions	0.0315	-0.0669
	(0.0566)	(0.0557)
Advanced Degree Indicator	0.206	0.0851
	(0.141)	(0.142)
Female Indicator	0.00879	−0.370**
	(0.165)	(0.157)
Minority Indicator	−0.286**	-0.0290
	(0.144)	(0.143)
Cohort Dummies	Yes	Yes
Wald χ^2	490.37	294.47
df	16	16
Subjects	849	849
Observations	849	849
Failures	269	147
Time at Risk	5,803.669	5,803.669
Log Likelihood	-767.840	-440.290

Notes. The sample includes individuals whose first job is wage employment. The time-to-event variables are tenure with the current employer and time to promotion, where exit from the current employer and promotion are treated as competing risks. Coefficients are reported from Weibull accelerated failure time models. Robust standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6: AFT Estimates of Tenure in Initial Occupation

Variables	Tenure in the Initial Occupation
Program Participation	0.298**
	(0.136)
Prior Self-Employment Experience Indicator	0.0380
	(0.185)
Prior Industry Exposure Indicator	0.0927
	(0.205)
Number of Prior Positions	-0.0203
	(0.0496)
Advanced Degree Indicator	0.189
	(0.129)
Female Indicator	-0.100
	(0.155)
Minority Indicator	-0.123
	(0.131)
Cohort Dummies	Yes
Wald χ^2	387.69
df	16
Subjects	795
Observations	795
Failures	212
Time at Risk	4,043
Log Likelihood	-611.885

Notes. The sample is restricted to individuals whose first job is wage employment. The model examines the duration from the start of initial employment to the first observed change in the first two digits of the O*NET code. Coefficients are reported from a Weibull accelerated failure time model. Robust standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 7: Program Participation and Compensation in First Full-Time Job by Number of Prior Positions

Variables	Log Annual Salary
Number of Prior Positions	-0.0199
	(0.0233)
Program Participation	0.0835**
	(0.0338)
Program Participation × Number of Prior Positions	0.0451*
	(0.0240)
Prior Self-Employment Experience Indicator	-0.0282
	(0.0535)
Prior Industry Exposure Indicator	0.00968
	(0.0507)
Advanced Degree Indicator	0.125***
	(0.0318)
Female Indicator	−0.124***
	(0.0429)
Minority Indicator	0.00448
	(0.0327)
Cohort Dummies	Yes
Observations	858
R-squared	0.0733

Notes. The sample includes individuals whose first job is wage employment. Number of Prior Positions is mean-centered, and the interaction term is constructed as the centered value of Number of Prior Positions multiplied by Program Participation. Robust standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 8: OLS Estimates for Selection into Program Participation

Variables	Program Participation
Prior Self-Employment Experience Indicator	-0.0313
	(0.0317)
Prior Industry Exposure Indicator	-0.0169
	(0.0344)
Number of Prior Positions	0.00244
	(0.00849)
Advanced Degree Indicator	-0.0841^{***}
	(0.0232)
Female Indicator	-0.00694
	(0.0269)
Minority Indicator	0.000245
	(0.0230)
Cohort Dummies	Yes
Observations	1,740
R-squared	0.111

Notes. This table presents OLS estimates of the likelihood that a student is selected into the program, using pre-application characteristics as explanatory variables. Logit regression results show similar coefficient signs and statistical significance. Robust standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 9: Logistic Regression Estimates for First Full-Time Job Outcomes (Matching)

Variables	**CEM**	**PSM**
Program Participation	-0.000864	0.193
	(0.261)	(0.509)
Prior Self-Employment Experience Indicator	0.0985	-0.200
	(0.364)	(0.630)
Prior Industry Exposure Indicator	-0.110	0.561
	(0.407)	(0.731)
Number of Prior Positions	0.0322	0.249^{*}
	(0.125)	(0.128)
Advanced Degree Indicator	-0.312	-0.998^{**}
	(0.257)	(0.468)
Female Indicator	-1.014^{**}	-1.120
	(0.420)	(0.710)
Minority Indicator	0.371	0.391
	(0.258)	(0.475)
Cohort Dummies	Yes	Yes
Observations	875	473
Wald χ^2	23.29	35.34
Log Likelihood	-251.766	-196.862

Notes. Column 1 reports results using CEM, and Column 2 reports results using PSM. For PSM, we estimate the propensity score for program participation using a logit model and implement one-to-one nearest-neighbor matching within common support, with a caliper of 0.05. Robust standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 10: OLS Estimates for Compensation in First Full-Time Job

Variables	**CEM**	**PSM**
Program Participation	0.0621*	0.276***
	(0.0367)	(0.101)
Prior Self-Employment Experience Indicator	0.00181	0.0793
	(0.0642)	(0.131)
Prior Industry Exposure Indicator	0.0289	-0.0717
	(0.0534)	(0.112)
Number of Prior Positions	-0.00834	0.00579
	(0.0215)	(0.0290)
Advanced Degree Indicator	0.159***	0.182**
	(0.0355)	(0.0822)
Female Indicator	−0.140***	0.0241
	(0.0504)	(0.0845)
Minority Indicator	-0.00643	-0.120
	(0.0362)	(0.0895)
Cohort Dummies	Yes	Yes
Observations	791	441
R-squared	0.1066	0.1763

Notes. The sample includes individuals whose first job is wage employment. Column 1 reports results using CEM, and Column 2 reports results using PSM. For PSM, we estimate the propensity score for program participation using a logit model and implement one-to-one nearest-neighbor matching within common support, with a caliper of 0.05. Robust standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 11: AFT Estimates of Tenure with Initial Employer (CEM)

Variables	Tenure with Initial Employer	Tenure to Promotion
Program Participation	0.359**	0.310*
	(0.150)	(0.162)
Prior Self-Employment Experience Indicator	-0.354	0.0151
	(0.238)	(0.351)
Prior Industry Exposure Indicator	0.142	0.229
	(0.225)	(0.256)
Number of Prior Positions	-0.00314	-0.0823
	(0.0719)	(0.0945)
Advanced Degree Indicator	0.226	0.201
	(0.151)	(0.168)
Female Indicator	-0.107	−0.447**
	(0.173)	(0.212)
Minority Indicator	−0.263*	0.0542
	(0.156)	(0.161)
Cohort Dummies	Yes	Yes
Wald χ^2	357.24	188.44
df	16	16
Subjects	785	785
Observations	785	785
Failures	261	137
Time at Risk	5,294.490	5,294.490
Log Likelihood	-726.640	-411.537

Notes. The sample includes individuals whose first job is wage employment. This table reports results using CEM. The time-to-event variables are tenure with the initial employer and time to promotion. Coefficients are reported from Weibull accelerated failure time models. Robust standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 12: AFT Estimates of Tenure with Initial Employer (PSM)

Variables	Tenure with Initial Employer	Tenure to Promotion
Program Participation	0.784***	0.484*
	(0.200)	(0.268)
Prior Self-Employment Experience Indicator	-0.217	0.196
	(0.279)	(0.446)
Prior Industry Exposure Indicator	0.495**	0.637
	(0.249)	(0.646)
Number of Prior Positions	-0.0562	−0.239**
	(0.0724)	(0.0959)
Advanced Degree Indicator	0.425**	0.460
	(0.211)	(0.317)
Female Indicator	0.0616	-0.311
	(0.229)	(0.281)
Minority Indicator	-0.209	−0.438*
	(0.228)	(0.256)
Cohort Dummies	Yes	Yes
Wald χ^2	201.68	151.92
df	16	16
Subjects	743	743
Observations	435	435
Failures	303	118
Time at Risk	4,556.335	4,556.335
Log Likelihood	-693.784	-324.722

Notes. The sample includes individuals whose first job is wage employment. This table reports results using PSM. For PSM, we estimate the propensity score for program participation using a logit model and implement one-to-one nearest-neighbor matching within common support, with a caliper of 0.05. The time-to-event variables are tenure with the initial employer and time to promotion. Coefficients are reported from Weibull accelerated failure time models. Robust standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 13: AFT Estimates of Tenure in Initial Occupation (Matching)

Variables	**CEM**	**PSM**
Program Participation	0.286**	0.757***
	(0.144)	(0.190)
Prior Self-Employment Experience Indicator	0.189	-0.0836
	(0.235)	(0.286)
Prior Industry Exposure Indicator	0.161	0.416
	(0.227)	(0.294)
Number of Prior Positions	-0.0506	-0.0144
	(0.0702)	(0.0670)
Advanced Degree Indicator	0.248*	0.397*
	(0.146)	(0.218)
Female Indicator	0.0227	0.287
	(0.175)	(0.250)
Minority Indicator	-0.110	0.398
	(0.148)	(0.248)
Cohort Dummies	Yes	Yes
Wald χ^2	304.73	180.21
df	16	16
Subjects	736	704
Observations	736	408
Failures	196	236
Time at Risk	3,802.701	3,713
Log Likelihood	-565.627	-536.462

Notes. The sample is restricted to individuals whose first job is wage employment. Column 1 reports results using CEM, and Column 2 reports results using PSM. For PSM, we estimate the propensity score for program participation using a logit model and implement one-to-one nearest-neighbor matching within common support, with a caliper of 0.05. The model examines the duration from the start of initial employment to the first observed change in the first two digits of the O*NET code. Coefficients are reported from a Weibull accelerated failure time model. Robust standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 14: Double Machine Learning Estimates of Program Participation on Initial Log Annual Salary

Variables	**Initial Log Annual Salary**		
	Double-LASSO	**DML-Random Forest**	**DML – XGBoost**
	(1)	**(2)**	**(3)**
Program Participation (= 0/1)	0.0726**	0.0906**	0.0839**
	(0.0334)	(0.0418)	(0.0337)
Observations	858	858	858

Notes. The sample includes individuals whose first job is wage employment. Columns 1–3 report double machine learning (DML) estimates of the average treatment effect using an interactive doubly robust regression model with five-fold cross-fitting. Column 1 uses ℓ_1-penalized regression on a high-dimensional set of covariates and their pairwise interactions, Column 2 uses random forests, and Column 3 uses XGBoost. Robust standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 15: Estimates for Compensation in First Full-Time Job

Variables	Log Annual Salary
Program Participation	0.354^{*}
	(0.204)
Prior Self-Employment Experience Indicator	-0.030
	(0.059)
Prior Industry Exposure Indicator	0.022
	(0.057)
Number of Prior Positions	-0.004
	(0.020)
Advanced Degree Indicator	0.137^{***}
	(0.037)
Female Indicator	-0.115^{**}
	(0.048)
Minority Indicator	-0.003
	(0.037)
Cohort Dummies	Yes
Observations	765
First-stage F-statistic	32.9

Notes. The sample includes individuals whose first job is wage employment. Program participation is instrumented by the log number of prior program participants who entered the university in the same admission year as the focal individual. Robust standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

FIGURE



Figure 1: Number of Recorded Participants and Applications by Year

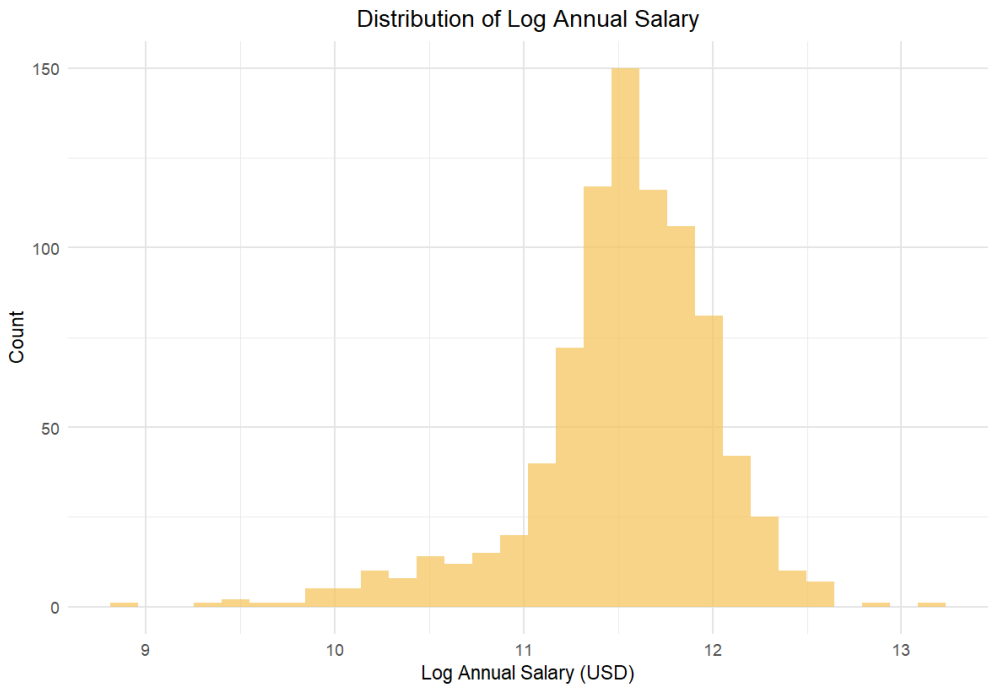


Figure 2: Annual Compensation Distribution Among Participants with Post-Program Full-Time Jobs

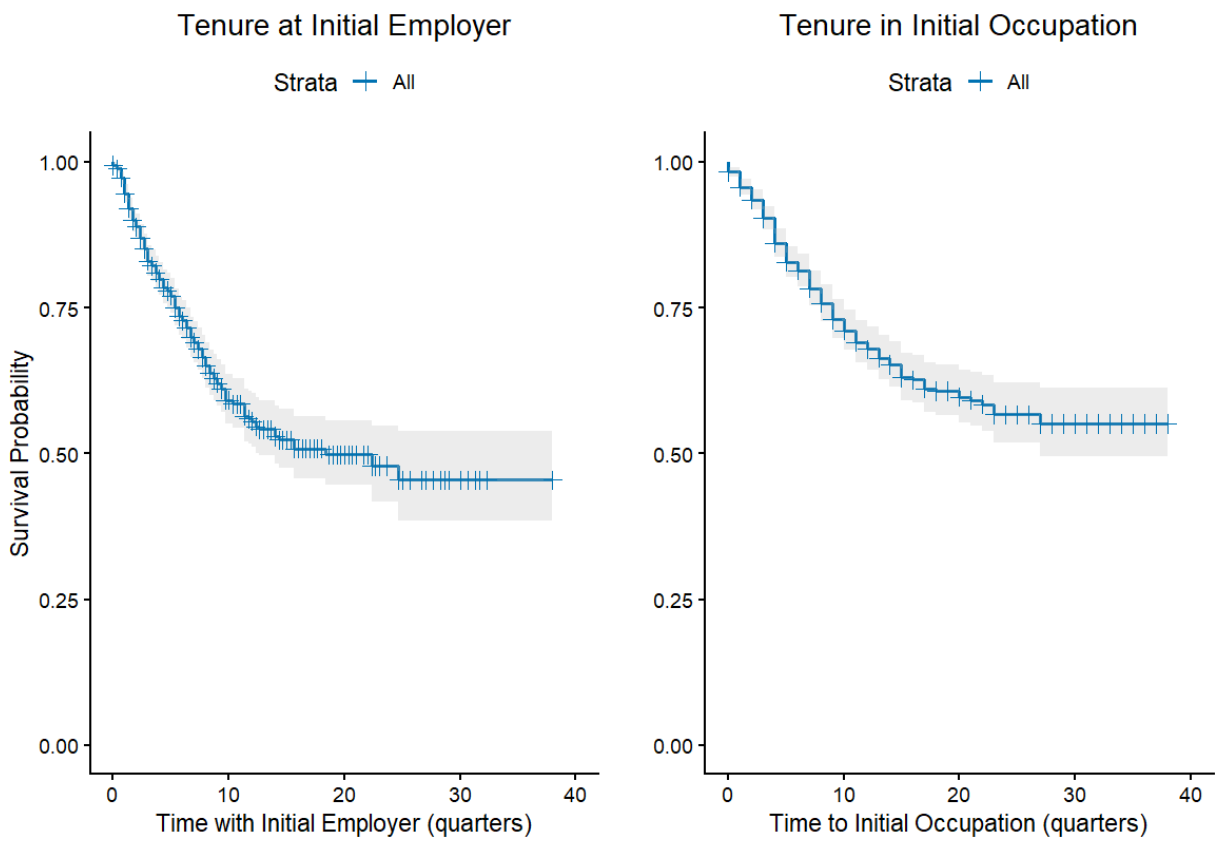


Figure 3: Kaplan–Meier Estimates of Career Transition

APPENDIX

Table A.1: OLS Estimates for Compensation in First Full-Time Job (Alternative Compensation Data)

Variables	Log Annual Salary
Program Participation	0.0773**
	(0.0374)
Prior Self-Employment Experience Indicator	0.0201
	(0.0553)
Prior Industry Exposure Indicator	0.123**
	(0.0560)
Number of Prior Positions	0.00282
	(0.0132)
Advanced Degree Indicator	0.0979***
	(0.0362)
Female Indicator	-0.0588
	(0.0478)
Minority Indicator	0.0273
	(0.0372)
Cohort Dummies	Yes
Observations	523
R-squared	0.0783

Notes. The sample includes individuals whose first job is wage employment. Salary data are measured as median total pay reported on Glassdoor. Robust standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.2: Cox Estimates of Initial Career Transition

Variables	External Mobility	Internal Promotion
Program Participation	0.807*	0.705**
	(0.104)	(0.125)
Prior Self-Employment Experience Indicator	1.281	1.097
	(0.235)	(0.284)
Prior Industry Exposure Indicator	0.941	0.813
	(0.171)	(0.220)
Number of Prior Positions	0.982	1.102
	(0.0489)	(0.0722)
Advanced Degree Indicator	0.807*	0.847
	(0.102)	(0.143)
Female Indicator	1.001	1.566**
	(0.147)	(0.290)
Minority Indicator	1.275*	1.026
	(0.163)	(0.174)
Cohort Dummies	Yes	Yes
Wald χ^2	10966.82	25.34
df	16	15
Prob $> \chi^2$	0.0000	0.0456
Subjects	849	849
Observations	849	849
Failures	269	147
Time at Risk	5,803.669	5,803.669
Log Likelihood	-1641.397	-864.823

Notes. The sample includes individuals whose first job is wage employment. Hazard ratios are reported from Cox proportional hazards models. Robust standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.3: Cox Estimates of Initial Occupation Switching

Variables	Occupation Switching
Program Participation	0.728**
	(0.106)
Prior Self-Employment Experience Indicator	0.938
	(0.187)
Prior Industry Exposure Indicator	0.941
	(0.203)
Number of Prior Positions	1.037
	(0.0544)
Advanced Degree Indicator	0.805
	(0.109)
Female Indicator	1.125
	(0.183)
Minority Indicator	1.152
	(0.159)
Cohort Dummies	Yes
Wald χ^2	10398.22
df	16
Prob $> \chi^2$	0.0000
Subjects	795
Observations	795
Failures	212
Time at Risk	4,043
Log Likelihood	-1306.664

Notes. The sample is restricted to individuals whose first job is wage employment. The model examines the duration from the start of initial employment to the first observed change in the first two digits of the O*NET code. Hazard ratios are reported from a Cox proportional hazards model. Robust standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.4: Logistic Regression Estimates for First Full-Time Job Outcomes (Excluding Repeat Participants)

Variables	First Full-Time Job
Program Participation	-0.0627
	(0.245)
Prior Self-Employment Experience Indicator	0.426
	(0.308)
Prior Industry Exposure Indicator	0.0115
	(0.366)
Number of Prior Positions	-0.0247
	(0.0942)
Advanced Degree Indicator	-0.332
	(0.242)
Female Indicator	-0.517
	(0.317)
Minority Indicator	0.488**
	(0.240)
Cohort Dummies	Yes
Observations	937
Wald χ^2	32.99
df	16
Prob $> \chi^2$	0.0074
Pseudo R-squared	0.0460
Log Likelihood	-274.095

Notes. The sample excludes individuals who participated in the program multiple times. Robust standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.5: OLS Estimates for Compensation in First Full-Time Job (Excluding Repeat Participants)

Variables	Log Annual Salary
Program Participation	0.0807**
	(0.0340)
Prior Self-Employment Experience Indicator	-0.0240
	(0.0551)
Prior Industry Exposure Indicator	0.00598
	(0.0522)
Number of Prior Positions	0.000765
	(0.0186)
Advanced Degree Indicator	0.119***
	(0.0324)
Female Indicator	−0.118***
	(0.0432)
Minority Indicator	0.00325
	(0.0330)
Cohort Dummies	Yes
Observations	847
F-statistic	4.66
df	16, 830
Prob $> F$	0.0000
R-squared	0.0672
Root MSE	0.4829

Notes. The sample includes individuals whose first job is wage employment and excludes individuals who participated in the program multiple times. Robust standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.6: AFT Estimates of Tenure with Initial Employer (Excluding Repeat Participants)

Variables	Tenure with Initial Employer	Tenure to Promotion
Program Participation	0.206	0.271*
	(0.145)	(0.150)
Prior Self-Employment Experience Indicator	-0.252	-0.0360
	(0.209)	(0.221)
Prior Industry Exposure Indicator	0.142	0.268
	(0.205)	(0.228)
Number of Prior Positions	0.0290	-0.0741
	(0.0571)	(0.0566)
Advanced Degree Indicator	0.198	0.0924
	(0.141)	(0.142)
Female Indicator	0.0228	−0.365**
	(0.165)	(0.158)
Minority Indicator	−0.286**	-0.00772
	(0.145)	(0.144)
Cohort Dummies	Yes	Yes
Wald χ^2	467.61	294.83
df	16	16
Prob $> \chi^2$	0.0000	0.0000
Subjects	838	838
Observations	838	838
Failures	268	146
Time at Risk	5,720.668	5,720.668
Log Likelihood	-762.320	-436.850

Notes. The sample includes individuals whose first job is wage employment and excludes individuals who participated in the program multiple times. The time-to-event variables are tenure with the current employer and time to promotion, where exit from the current employer and promotion are treated as competing risks. Coefficients are reported from Weibull accelerated failure time models. Robust standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.7: AFT Estimates of Tenure in Initial Occupation (Excluding Repeat Participants)

Variables	Tenure in the Initial Occupation
Program Participation	0.285**
	(0.138)
Prior Self-Employment Experience Indicator	0.0509
	(0.189)
Prior Industry Exposure Indicator	0.0829
	(0.208)
Number of Prior Positions	-0.0222
	(0.0503)
Advanced Degree Indicator	0.181
	(0.130)
Female Indicator	-0.0975
	(0.156)
Minority Indicator	-0.119
	(0.132)
Cohort Dummies	Yes
Wald χ^2	382.94
df	16
Prob $> \chi^2$	0.0000
Subjects	785
Observations	785
Failures	210
Time at Risk	3,989
Log Likelihood	-605.020

Notes. The sample includes individuals whose first job is wage employment and excludes individuals who participated in the program multiple times. The model examines the duration from the start of initial employment to the first observed change in the first two digits of the O*NET code. Coefficients are reported from a Weibull accelerated failure time model. Robust standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.8: OLS Estimates for Compensation in First Full-Time Job (Outlier Robustness)

Variables	Trim 1%/99%	Trim 5%/95%	Trim 10%/90%
Program Participation	0.0856***	0.0854***	0.0673***
	(0.0304)	(0.0249)	(0.0201)
Prior Self-Employment Experience Indicator	-0.0493	-0.00250	0.0174
	(0.0465)	(0.0355)	(0.0297)
Number of Prior Positions	0.00569	0.00502	0.00319
	(0.0101)	(0.00784)	(0.00644)
Advanced Degree Indicator	0.140***	0.0962***	0.0478**
	(0.0296)	(0.0239)	(0.0196)
Female Indicator	−0.104***	−0.0725**	−0.0790***
	(0.0385)	(0.0309)	(0.0249)
Minority Indicator	0.0238	0.00261	-0.0146
	(0.0304)	(0.0242)	(0.0195)
Cohort Dummies	Yes	Yes	Yes
Observations	844	774	688
F-statistic	5.95	4.85	4.46
Prob $> F$	0.0000	0.0000	0.0000
R-squared	0.0927	0.0808	0.0835
Root MSE	0.4315	0.3298	0.2521

Notes. The sample includes individuals whose first job is wage employment. The dependent variable is log salary in the first full-time job. Columns report results after trimming the treatment and control groups separately at the 1st/99th, 5th/95th, and 10th/90th percentiles, respectively. Robust standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.9: AFT Estimates of Initial Career Transition

Variables	External Mobility	Internal Promotion
Program Participation	0.288**	0.323**
	(0.144)	(0.153)
Prior Self-Employment Experience Indicator	-0.263	-0.0974
	(0.211)	(0.218)
Prior Industry Exposure Indicator	0.178	0.267
	(0.208)	(0.225)
Number of Prior Positions	0.0303	-0.0661
	(0.0573)	(0.0569)
Advanced Degree Indicator	0.239	0.100
	(0.145)	(0.148)
Female Indicator	0.0775	−0.368**
	(0.168)	(0.165)
Minority Indicator	−0.256*	0.0232
	(0.144)	(0.145)
Cohort Dummies	Yes	Yes
Job Family Dummies	Yes	Yes
Wald χ^2	615.10	412.72
df	34	34
Prob $> \chi^2$	0.0000	0.0000
Subjects	847	847
Observations	847	847
Failures	269	147
Time at Risk	5,768.669	5,768.669
Log Likelihood	-750.772	-428.674

Notes. The sample includes individuals whose first job is wage employment. Coefficients are reported from Weibull accelerated failure time models. Robust standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.10: Balance Test Between Full Sample and Missing-Value Subsample

Variables	Participation Sample	Subsample in Application Record	Difference	p-value
Prior Self-Employment Experience	0.209	0.272	-0.063^{**}	0.041
Prior Work Experience	0.866	0.884	-0.018	0.436
Number of Prior Positions	2.539	2.775	-0.236	0.111
Advanced Degree Indicator	0.417	0.428	-0.011	0.759
Female Indicator	0.242	0.254	-0.012	0.692
Minority Indicator	0.517	0.533	-0.016	0.654

Notes. This table compares observable characteristics between the full sample of program participants and the subsample reported in the application data. Columns report group means, mean differences, and p-values from Welch two-sample t-tests. The difference is calculated as the mean of the full sample minus the mean of the subsample.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.