Entrepreneurship Education and Career Trajectories

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 startup incubator at a technology-based university, this study examines the impact of an entrepreneurship education program by comparing the post-graduation career trajectories of accepted and non-admitted 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 makret outcome

1 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 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 influence participants' careers, including the careers of those in conventional professions such as law, investment management, and academia (Drake, 2022). Participants reported that the experience shaped their career choices, broadened their views of 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 and reduce academic performance and educational attainment 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. Existing evidence remains mixed, in part because prior research has focused primarily on entrepreneurial intentions, entry into entrepreneurship, and venture performance (Hsu et al., 2007; Von Graevenitz et al., 2010; Eesley and Lee, 2021). This focus leaves underexplored a broader and arguably more representative group of students: those who receive entrepreneurship education but ultimately enter wage employment. Consequently, it remains unclear whether entrepreneurship education improves post-graduation job quality, career stability, and economic returns beyond its effects on entrepreneurial entry.

To answer this question, we examine the career outcomes of individuals who applied to a long-standing entrepreneurship initiative at a leading technology-based university. Established in 2014, the program provides an immersive summer experience in venture creation, supported by seed funding and intensive mentorship. The initiative is broadly inclusive, attracting participants from all academic levels as well as faculty, researchers, and alumni. Our sample covers applicant cohorts from 2014 through 2023. We draw on administrative records from the program, including application data and participation records. Our empirical strategy compares program participants with applicants who were not admitted, as both groups demonstrated strong entrepreneurial motivation by applying to the program. We manually link these individuals to their online résumé profiles and extract job histories to construct post-program career trajectories observed through April 2024. Our data allow us to extend the existing literature in several ways. First, the university-wide nature of the program enables us to capture entrepreneurial engagement among a broad and diverse population, rather than students selected from specific colleges, majors, or entrepreneurship courses. Second, the longitudinal structure of the data allows us to examine realized post-program career paths and labor market outcomes, complementing prior work that often relies on short-term measures such as entrepreneurial intentions or immediate startup outcomes. Third, résumé-based career histories provide granular information on job transitions, employer tenure, occupational choices, and earnings-related indicators, allowing us to observe career trajectories more comprehensively than self-reported survey data.

We first examine how participation in entrepreneurship education is associated with individuals' initial career choices after the program, including whether they pursue entrepreneurial activities or enter wage employment. Conditional on entering wage employment, we then study the quality of individuals' first full-time job matches. We argue that entrepreneurship education may improve subsequent job-match quality by exposing participants to broad and diverse work demands before labor market entry. This argument builds on the "jack-of-all-trades" perspective, which views entrepreneurs as generalists with balanced portfolios of skills across multiple domains rather than as individuals with highly specialized human capital (Åstebro and Thompson, 2011; Lazear,

2004). Because startups are typically resource-constrained and rely on small teams (Aldrich, 1999; Rosen, 1983), individuals in entrepreneurial settings often perform a wide range of tasks and assume substantial responsibility. Entrepreneurship education simulates these conditions by exposing participants 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). We propose that such exposure helps participants accumulate broad human capital, better understand different work roles, and gain clearer insight into their own abilities and preferences (Papageorgiou, 2014). As a result, participants may be better able to identify wage-employment positions that align with their skills and interests, thereby improving job-match quality upon labor market entry.

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 create value not only by increasing the likelihood of venture success, but also by helping participants assess their fit with entrepreneurship. Among those who initially enter wage employment, we examine compensation 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 salaries that are 8.27% higher in their first jobs. They also exhibit longer tenure with their first employers and in their initial occupation types. 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, sensitivity checks, and specifications that include additional control variables and alternative compensation outcome measures.

This study makes two main theoretical contributions. First, it extends the literature on entrepreneurship education by shifting attention from entrepreneurial intentions and entry to broader career outcomes. Prior research has largely examined whether entrepreneurship education af-

fects students' entrepreneurial intentions or entry into entrepreneurship (Eesley and Lee, 2021; Lyons and Zhang, 2018; Souitaris et al., 2007; Peterman and Kennedy, 2003; Von Graevenitz et al., 2010), while its implications for subsequent career trajectories remain less understood. Even studies of post-program performance tend to focus on venture-level outcomes such as survival, funding, or growth. Because many entrepreneurs eventually transition into paid employment, it is important to examine how entrepreneurship education shapes careers beyond entrepreneurship. Our study addresses this gap by linking entrepreneurship education to non-entrepreneurial labor market outcomes. Second, this study contributes to the literature on entrepreneurship and labor market outcomes by distinguishing university-based entrepreneurship education from actual entrepreneurial experience. Prior work finds mixed evidence on the wage and career consequences of entrepreneurial experience (Campbell, 2013; Luzzi and Sasson, 2016; Baptista et al., 2012; Mahieu et al., 2022), partly because entrepreneurial experience is difficult to separate from selection into entrepreneurship. Entrepreneurs may differ from wage employees in risk tolerance, intrinsic motivation, autonomy preferences, and attachment to organizational careers. Employers may also view entrepreneurial experience as a signal of weaker fit with wage employment. By studying entrepreneurship education before labor market entry, this paper examines a lower-risk form of entrepreneurial exposure that is less likely to carry the same employer-side penalties. This setting allows us to assess whether entrepreneurial knowledge, skills, and mindsets shape subsequent wage-employment outcomes while mitigating key selection concerns.

2 Research Context

An ideal empirical setting should feature a well-developed entrepreneurship program that provides intensive, economically meaningful training while allowing credible comparisons between participants and otherwise similar nonparticipants. Simple comparisons with the broader student population may suffer from 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 address-

ing this challenge because 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 entrepreneurship education initiative at a leading science and engineering university. 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, who may apply individually or in teams. Applicants submit an online form and complete an interview, with about one-sixth of teams admitted on average. Following (Lyons and Zhang, 2018), we define the counterfactual as applicants who sought entry into the program but were not admitted, and we use these non-admitted applicants as the control group. Both admitted and non-admitted applicants demonstrated entrepreneurial interest by applying to the program. 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 in which selected teams focus exclusively on developing their ventures. Upon acceptance, each team receives an initial seed grant of $4,000–$5,000 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. The program culminates in a Demo Day, a university-sponsored event at which teams present their ventures to potential investors, industry partners, and the broader entrepreneurial community.

3 Data and Measurements

In this study, we draw on two novel data sources. The first consists of administrative records from the university entrepreneurship program, comprising two related datasets: an application

dataset that records individuals who applied to the program and a participation dataset that identifies individuals who ultimately enrolled as startup founders. Overall, the application dataset includes 1,536 applicants through 2023, of whom 340 were admitted and 1,196 were not. By comparison, the participation dataset records 1,241 unique individuals who enrolled in the program by 2023. Some information is missing because of record-keeping limitations, post-application changes in team composition, and incomplete responses to follow-up emails sent after submission. The second data source is online résumé data from Revelio, which provide information on individuals' educational backgrounds, employment histories, demographic characteristics, and estimated salaries. These data are right-censored as of April 1, 2024. We match individuals from the program records to profiles in the Revelio database. This matching process yields 919 participants and 915 non-admitted applicants. Our analysis focuses exclusively on full-time employment reported on individuals' résumés that began after program completion, ensuring that all observed labor market outcomes occur after the relevant treatment or assignment point.[1] 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 416 participants and 544 individuals in the control group with at least one full-time job beginning after their application.

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 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. Next, we focus on individuals whose first employment status is classified as

[1] Full-time employment is identified based on job titles reported on résumés. Internships, co-op positions, part-time roles, on-campus activities, academic research positions, startup projects associated with the entrepreneurship program, and other non-full-time positions are excluded from the analysis.

wage 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. Compensation is measured using estimated annual compensation inferred from Revelio Labs data.[2] We interpret higher estimated salaries as indicative of better job matches because they reflect the market value of the worker–job pairing. We then use résumé profiles to identify career transitions along two dimensions: employer tenure and occupation tenure. Employer tenure is defined as the duration of employment with the current employer, ending when an individual moves to a different employer, enters self-employment, or exits employment; we also examine time to promotion as a competing time-to-event outcome. 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. Furthermore, to capture underlying individual-occupation matches, 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.[3]

We also 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 and an indicator for whether the individual's ethnicity is classified as a minority (non-White). Educational variables capture attainment and credentials beyond the master's level, including MBA and doctoral degrees. We further measure pre-program industry experience using indicators for prior entrepreneurship experience and prior industry ex-

[2] 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.

[3] An occupational switch is identified when the first two digits of an individual's O*NET occupation code change across different positions.

posure. These are defined, respectively, as binary variables indicating whether the individual had ever been self-employed or had any wage-employment experience[4] as of April of the cohort year in which the individual applied to the program. Finally, we measure the number of distinct positions an applicant held before applying, including self-employment, to capture the breadth of their prior industry exposure.

4 Model Specification

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

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

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[5]. 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 by adopting an accelerated failure time (AFT) model based on Harhoff and Wagner (2009), with a Weibull distribution[6]. This specification allows coefficients to be interpreted as changes in time to failure: negative coefficients indicate shorter durations, or faster transitions, while positive coefficients indicate longer durations[7]. In the current-employer tenure analysis, the dependent variable is tenure with the initial employer, which is measured in half-years, and promo-

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

[5]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.

[6]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.

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

tion 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. In addition to the baseline specification, we employ coarsened exact matching (CEM) and one-to-one nearest-neighbor propensity score matching (PSM) as robustness checks. These methods improve comparability between the treatment and control groups by restricting the analysis to observationally similar applicants while retaining a sufficiently large sample. Matching on these characteristics improves covariate balance and helps reduce concerns that the estimated effects are driven by pre-existing differences rather than program participation.

5 Results and Analysis

We first compare program participants with a control group to assess the prevalence of entrepreneurship relative to wage employment. Table 1 reports the baseline, CEM, and PSM estimates from logit models estimating differences in initial employment status between program participants and non-admitted applicants. The results indicate a negative but statistically insignificant difference 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 that entrepreneurship education may help individuals better assess their fit for entrepreneurship, rather than necessarily increasing their likelihood of starting a venture.

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 2 suggests that, relative to non-admitted applicants, program participants earn approximately 8.27% higher salaries in their initial job placements in the baseline specification, a significant difference at the 5% level. 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, 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 also examine how career transition patterns differ between program participants and nonparticipants. Table 3 reports estimates of the association between program participation and the timing of individuals' first transition from their initial full-time employment. The baseline estimate suggests that program participation is marginally associated with 26.8% longer tenure with the initial employer, 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 baseline estimate also indicates that program participation is marginally associated with a 33.3% longer duration until first promotion. 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 4, indicate that program participants exhibit 34.7% significantly longer tenure in their initial occupation than non-admitted applicants in the control group, 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 employment, relative to non-admitted applicants in our sample. Together, these results provide empirical evidence that program participants achieve higher job-match quality in their first

full-time job placements.

We also 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. We measure the breadth of students' pre-program industry exposure using the number of prior employment positions, 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 5 reports the results. Program participation remains positively and significantly associated with first full-time job salary. However, the coefficient on number of prior positions is negative, though statistically insignificant. 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. This suggests that the wage premium associated with entrepreneurship education is larger for students with broader prior industry

exposure. Specifically, for a student with one additional prior industry 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.

6 Robustness Checks

We conduct several robustness checks to assess the sensitivity of our findings. We begin by relaxing the linear functional-form restriction in the baseline wage regressions using a double machine learning (DML) framework. Specifically, 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. We implement three nuisance-function estimators: (i) LASSO using a high-dimensional set of covariates and pairwise interactions, (ii) random forests, and (iii) XGBoost. The baseline controls include pre-application characteristics, demographic variables, major fixed effects, and cohort fixed effects, yielding 67 controls. For the LASSO specification, we further include all pairwise interactions, producing 613 high-dimensional controls from which the model selects a sparse subset. 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 7.5% under LASSO, 8.7% under XGBoost, and 9.5% under random forests, with all estimates statistically significant at the 5% level. Next, we examine whether the career-transition results are affected by occupational heterogeneity. Because career mobility may vary across occupations (Huang and Zhang, 2016), we add dummy variables for occupational groups, defined using the first two digits of the O*NET code, and re-estimate the models for tenure with the initial employer. The results remain consistent with the baseline estimates. We do not include these occupational controls in the wage analysis or in the analysis of tenure within the initial occupation, because program participation may itself affect en-

try into particular occupations or industries. Controlling for such potential post-treatment variables would introduce "bad controls" (Angrist and Pischke, 2009). We also assess the career-transition results using Cox proportional hazards models. Program participation is associated with a 20.1% lower hazard of exiting the initial employer, implying that participants remain with their initial employer longer, conditional on having stayed up to a given point in time. Participants also exhibit a significantly lower hazard of switching out of their initial occupation, consistent with the baseline finding that they remain longer in their initial occupational category. We further examine whether the findings are driven by repeated exposure to the program. Because 2.1% of participants have multiple participation records, we exclude these individuals and re-estimate the models. The results remain directionally and statistically similar to the baseline estimates. To address concerns about extreme salary values, we separately trim the treatment and control groups at alternative percentiles, including the 1st and 99th, 5th and 95th, and 10th and 90th percentiles of the salary distribution. The estimated effects remain similar in magnitude and statistical significance across all trimming specifications. Finally, we validate the compensation results using an alternative measure based on median total pay reported on Glassdoor. Glassdoor data consist of self-reported compensation records submitted by employees and job seekers and have been used in prior research (Babenko and Sen, 2014; Forderer and Burtch, 2025; Hampole et al., 2026; Li, 2025). We infer median total pay from applicants' online résumé profiles and match 61% of the applicant sample to Glassdoor salary records. Using this alternative compensation measure, we find that admitted applicants earn approximately 7.73% higher wages in their first post-application job, a statistically significant estimate that is similar to the baseline result. Taken together, these analyses indicate that the main results are robust across alternative estimation strategies, additional controls, sample restrictions, outlier treatments, and compensation measures.

7 Discussion

This study provides new evidence on how university-based entrepreneurship programs shape students' career development beyond new venture creation. Using matched program records and

online résumé profiles, we compare program participants with comparable non-admitted applicants. We find that program participation is not significantly associated with a higher likelihood of self-employment in the first job after program completion. However, among graduates who enter wage employment, participants experience better job matches and stronger labor-market performance: they remain longer with their first employers, are more likely to stay within the same occupational classification, and earn higher estimated salaries. These findings have practical implications for universities, students, and employers. For universities, entrepreneurship programs should not be evaluated only by start-up creation or self-employment rates, but also by broader outcomes such as job-match quality, compensation, and career stability. For students, entrepreneurship education may be valuable even without immediate plans to found a start-up, as it can support better first-job choices. For employers, program participants may represent a valuable talent pool, with stronger job fit, retention, and skills such as initiative, adaptability, and cross-functional thinking. Overall, university entrepreneurship programs create value not only through venture formation but also by improving wage-employment outcomes.

References

Aldrich, H. (1999). *Organizations evolving*. Sage.

Angrist, J. D. and Pischke, J.-S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Åstebro, T. and Thompson, P. (2011). Entrepreneurs, jacks of all trades or hobos? *Research policy*, 40(5):637–649.

Babenko, I. and Sen, R. (2014). Money left on the table: An analysis of participation in employee stock purchase plans. *The Review of Financial Studies*, 27(12):3658–3698.

Baptista, R., Lima, F., and Preto, M. T. (2012). How former business owners fare in the labor market? job assignment and earnings. *European Economic Review*, 56(2):263–276.

Bjorvatn, K., Cappelen, A. W., Sekei, L. H., Sørensen, E. Ø., and Tungodden, B. (2020). Teaching through television: Experimental evidence on entrepreneurship education in tanzania. *Management Science*, 66(6):2308–2325.

Campbell, B. A. (2013). Earnings effects of entrepreneurial experience: Evidence from the semiconductor industry. *Management Science*, 59(2):286–304.

Card, D. (1999). The causal effect of education on earnings. In *Handbook of Labor Economics*, volume 3, pages 1801–1863. Elsevier.

Cohen, W. M. and Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 35(1):128–152.

Cox, D., Hinkley, D., Rubin, D., and Silverman, B. (1984). *Monographs on statistics and applied*

probability. Springer.
Dobrev, S. D. and Barnett, W. P. (2005). Organizational roles and transition to entrepreneurship. *Academy of Management Journal*, 48(3):433–449.
Drake, D. (2022). Can early entrepreneurial education make a difference in your life?
Eesley, C. and Wu, L. (2020). For startups, adaptability and mentor network diversity can be pivotal: Evidence from a randomized experiment on a mooc platform. *Mis Quarterly*, 44(2):661–698.
Eesley, C. E. and Lee, Y. S. (2021). Do university entrepreneurship programs promote entrepreneurship? *Strategic Management Journal*, 42(4):833–861.
Elfenbein, D. W., Hamilton, B. H., and Zenger, T. R. (2010). The small firm effect and the entrepreneurial spawning of scientists and engineers. *Management Science*, 56(4):659–681.
Folta, T. B., Delmar, F., and Wennberg, K. (2010). Hybrid entrepreneurship. *Management science*, 56(2):253–269.
Forderer, J. and Burtch, G. (2025). Estimating career benefits from online community leadership: evidence from stack exchange moderators. *Management Science*, 71(3):2443–2466.
Fredriksson, P., Hensvik, L., and Skans, O. N. (2018). Mismatch of talent: Evidence on match quality, entry wages, and job mobility. *American Economic Review*, 108(11):3303–3338.
Gompers, P., Lerner, J., and Scharfstein, D. (2005). Entrepreneurial spawning: Public corporations and the genesis of new ventures, 1986 to 1999. *The journal of Finance*, 60(2):577–614.
Hampole, M., Truffa, F., and Wong, A. (2026). Peer effects and the gender gap in corporate leadership: Evidence from mba students. *The Quarterly Journal of Economics*, page qjag015.
Harhoff, D. and Wagner, S. (2009). The duration of patent examination at the european patent office. *Management Science*, 55(12):1969–1984.
Hsu, D. H., Roberts, E. B., and Eesley, C. E. (2007). Entrepreneurs from technology-based universities: Evidence from mit. *Research policy*, 36(5):768–788.
Huang, P. and Zhang, Z. (2016). Participation in open knowledge communities and job-hopping. *MIS quarterly*, 40(3):785–806.
Jackson, C. K. (2013). Match quality, worker productivity, and worker mobility: Direct evidence from teachers. *Review of Economics and Statistics*, 95(4):1096–1116.
Jovanovic, B. (1984). Matching, turnover, and unemployment. *Journal of political Economy*, 92(1):108–122.
Katz, J. A. (2003). The chronology and intellectual trajectory of american entrepreneurship education: 1876–1999. *Journal of business venturing*, 18(2):283–300.
Lazear, E. P. (2004). Balanced skills and entrepreneurship. *American Economic Review*, 94(2):208–211.
Levine, R. and Rubinstein, Y. (2017). Smart and illicit: who becomes an entrepreneur and do they earn more? *The Quarterly journal of economics*, 132(2):963–1018.
Li, N. (2025). Labor market peer firms: understanding firms' labor market linkages through employees' internet "also viewed" firms. *Review of Accounting Studies*, 30(1):384–435.
Luzzi, A. and Sasson, A. (2016). Individual entrepreneurial exit and earnings in subsequent paid employment. *Entrepreneurship Theory and Practice*, 40(2):401–420.
Lyons, E. and Zhang, L. (2018). Who does (not) benefit from entrepreneurship programs? *Strategic Management Journal*, 39(1):85–112.
Mahieu, J., Melillo, F., and Thompson, P. (2022). The long-term consequences of entrepreneurship: Earnings trajectories of former entrepreneurs. *Strategic Management Journal*, 43(2):213–236.
Neal, D. (1999). The complexity of job mobility among young men. *Journal of labor Economics*,

17(2):237–261.
Papageorgiou, T. (2014). Learning your comparative advantages. *Review of Economic Studies*, 81(3):1263–1295.
Peterman, N. E. and Kennedy, J. (2003). Enterprise education: Influencing students' perceptions of entrepreneurship. *Entrepreneurship Theory and Practice*, 28(2):129–144.
Rosen, S. (1983). Specialization and human capital. *Journal of Labor Economics*, 1(1):43–49.
Shane, S. (2000). Prior knowledge and the discovery of entrepreneurial opportunities. *Organization Science*, 11(4):448–469.
Shane, S. (2003). A general theory of entrepreneurship: The individual-opportunity nexus. In *A General theory of entrepreneurship*. Edward Elgar Publishing.
Souitaris, V., Zerbinati, S., and Al-Laham, A. (2007). Do entrepreneurship programmes raise entrepreneurial intention of science and engineering students? the effect of learning, inspiration and resources. *Journal of Business venturing*, 22(4):566–591.
Von Graevenitz, G., Harhoff, D., and Weber, R. (2010). The effects of entrepreneurship education. *Journal of Economic behavior & organization*, 76(1):90–112.

Tables

Table 1: Logistic Regression Estimates for First Full-Time Employment Outcomes

Variables	**Baseline**	**CEM**	**PSM**
Program Participation	-0.0967	-0.000864	0.193
	(0.245)	(0.261)	(0.509)
Control Variables	Yes	Yes	Yes
Cohort Dummies	Yes	Yes	Yes
Observations	948	875	473
Wald χ^2	32.65	23.29	35.34
Log Likelihood	-275.193	-251.766	-196.862

Notes. Columns report the baseline estimate, coarsened exact matching (CEM) estimate, and one-to-one nearest-neighbor propensity score matching (PSM) estimate, respectively. For PSM, the propensity score is estimated using a logit model 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 2: OLS Estimates for Compensation in First Full-Time Employment

Variables	**Baseline**	**CEM**	**PSM**
Program Participation	0.0827**	0.0621*	0.276***
	(0.0337)	(0.0367)	(0.101)
Control Variables	Yes	Yes	Yes
Cohort Dummies	Yes	Yes	Yes
Observations	858	791	441
R-squared	0.0674	0.1066	0.1763

Notes. The sample includes individuals whose first job is wage employment. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3: AFT Estimates of Tenure with Initial Employer

	Baseline		**CEM**		**PSM**	
Variables	Initial Employer	Promotion	Initial Employer	Promotion	Initial Employer	Promotion
Program Participation	0.237*	0.288*	0.359**	0.310*	0.784***	0.484*
	(0.144)	(0.148)	(0.150)	(0.162)	(0.200)	(0.268)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Cohort Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Wald χ^2	490.37	294.47	357.24	188.44	201.68	151.92
df	16	16	16	16	16	16
Observations	849	849	785	785	435	435
Failures	269	147	261	137	303	118

Notes. The sample includes individuals whose first job is wage employment. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4: AFT Estimates of Tenure in Initial Occupation

Variables	**Baseline**	**CEM**	**PSM**
Program Participation	0.298**	0.286**	0.757***
	(0.136)	(0.144)	(0.190)
Control Variables	Yes	Yes	Yes
Cohort Dummies	Yes	Yes	Yes
Wald χ^2	387.69	304.73	180.21
df	16	16	16
Observations	795	736	408
Failures	212	196	236

Notes. The sample is restricted to individuals whose first job is wage employment. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: Program Participation and Compensation in First Full-Time Employment 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)
Control Variables	Yes
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. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.