Early Work Exposure and Long-Term STEM Retention: Experimental Evidence from Engineering Co-op

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March 26, 2026

Abstract

Retaining trained workers in STEM occupations is critical for sustaining innovation capacity, yet roughly half of U.S.-educated STEM graduates leave STEM jobs within a decade of graduation. A longstanding principle of applied-science education holds that the blend and timing of academic training and professional work experience improves career outcomes, raising the possibility that this sequencing may also shape long-run retention. However, causal evidence on how the timing of such exposure affects long-run retention is scarce. We study this question using a field experiment involving 1,503 engineering undergraduates enrolled in a mandatory cooperative education program who were randomly assigned to begin their first six-month professional placement either in their second or third year of study, holding fixed the quantity and quality of work experience and academic training. Students receiving earlier professional exposure persist in STEM jobs five years after graduating. We find no evidence that early exposure improves academic performance or leads to being re-hired permanently, inconsistent with skill-based or network-based explanations. Instead, earlier exposure raises the likelihood that students switch engineering specialties during college, consistent with improved information about career fit. The results show that earlier exposure to professional work experience during college can have a long-run effect on STEM workforce retention through improved matching. Codes: J2, I21, I26, O3

Keywords: STEM pipeline, Engineering, Field Experiment.

Boudreau: Northeastern University and NBER (e-mail: kevin@northeastern.edu); Marx: Cornell SC Johnson College of Business and NBER (e-mail: mmarx@cornell.edu). We appreciate comments from seminar participants at the NBER productivity seminar, the Duke Field Experiments Conference, ESMT, Arizona State University, Harvard University, the Roundtable for Engineering Entrepreneurship Research (REER), the University of Maryland, and Boston University. This work was conducted with financial support and advice from the Research Institute for Experiential Learning Science (RIELS); and we are especially grateful for advice and support from Susan Ambrose and Cidgem Talgar and colleagues Tony Armelin, John Bielaus, Esther Chewning, Roy Dalsheim, Joy Erb, Janna Ferguson, Rana Glasgal, Mary Kane, Shane Karcz, Laura Kenney, Candace Martel, Lorraine Mountain, Charles Price, Chris White, and Ellen Zierk. We also thank Muyang Zhou and Bochau Sun for research assistance. We would also like to acknowledge financial support from Boston University and Northeastern DMSB. The views expressed are those of the authors alone and do not necessarily reflect those of the institutions, funders or supporters and advisors involved with this study. Errors are ours.

1 Introduction

Sustaining a skilled domestic STEM workforce is central to long-run innovation, productivity growth, and economic competitiveness across advanced economies. Yet in many countries—and particularly in the United States—a substantial share of individuals trained in STEM fields do not remain in STEM occupations over the course of their careers. In the United States, roughly half of STEM graduates leave STEM jobs within ten years of graduation (National Science Board, 2020; Xie & Killewald, 2012)—a "leaky pipeline." At the same time, domestic education systems often supply only a fraction of national demand for STEM workers, increasing reliance on international talent and raising concerns about the effectiveness of existing training investments (National Academies of Sciences, Engineering, and Medicine, 2021). While policy discussions frequently focus on expanding STEM enrollment and degree production, far less is known about how the structure of STEM training affects long-run retention in applied STEM work. *Retention in STEM occupations is a natural outcome in this context, as it captures whether investments in training translate into sustained participation in applied scientific work.*

A natural place to look for such effects is the structure of training itself. A longstanding tenet of applied-science education holds that the blend—and, in particular, the timing—of academic instruction and professional experience shapes the development of applied scientists and engineers. In this view, early exposure to professional practice reinforces classroom learning, provide a concrete context for abstract concepts, and motivate more purposeful engagement with subsequent coursework. Dating back to nineteenth-century land-grant colleges in the United States and the Technische Hochschulen in Germany, this principle has guided engineering education across contexts—from laboratory courses and design studios to clinical rotations, internships, and cooperative education programs (Calhoun, 1960; Layton, 1971; Seely, 1999; Kolb, 1984; Schön, 1983). More broadly, this reflects a general question in human capital development: how the sequencing of formal training and practical experience shapes workers' skills, expectations, and career choices. *If the integration of theory and practice shapes how individuals develop as engineers, it may also influence whether they remain in STEM careers over time.* These questions are central to how post-secondary training systems shape the development and allocation of skilled workers.

Despite this long-standing emphasis in engineering education and related scholarship, there is little causal evidence on whether—and how—the timing of professional experience during training affects long-run career outcomes, including retention in STEM. Further, in addition to this developmental view of blending academics and exposure to practical experience, several other mechanisms or pathways could plausibly be affected by this early blend and exposure to practicum and practice.

One additional mechanism, rooted in labor and education economics, relates information and matching: individuals choose majors and careers under tremendous uncertainty, and early professional experience provides a rich signal about person-field fit. When such information arrives before substantial field-specific investments accumulate, it might enable individuals to reallocate toward better-matched fields at lower cost.

Another, drawn from research on labor markets and social networks, emphasizes opportunity access: earlier exposure to professional environments may facilitate the accumulation of workplace relationships and referral networks, easing entry into the labor market through employer connections. These three perspectives generate sharply different empirical predictions about how timing should affect academic performance, job opportunities, and field-switching behavior.

This paper investigates whether the blend and timing of professional work experience affects long-run retention in STEM occupations, and if so, through which mechanisms. We consider three channels: effects on human capital development during academic training (as emphasized in the engineering education literature), effects on access to early career opportunities and labor market entry (as emphasized in research on professional networks), and effects on learning about career fit and the matching of workers to specializations (as emphasized in the economics of education and labor markets).

We address these questions using a large-scale field experiment embedded in a mandatory cooperative education program at a major research university. The study follows 1,503 engineering undergraduates across six fields of specialization (Biological, Chemical, Civil, Computer, Electrical, and Mechanical Engineering) in cohorts enrolling between 2009 and 2014. Individuals were randomly assigned to begin their first six-month professional work placement either in their second or third year of study. Because all students complete the same number of work terms drawn from a

common employer pool and satisfy identical academic requirements, this design isolates the causal effect of the timing of professional exposure—holding fixed the quantity and institutional quality of work experience and formal educational training. Working in close cooperation with the institution, we assemble a rich dataset linking administrative records on academic performance, course enrollment, and work placements to pre-college characteristics and ten years of post-graduation employment histories.

We find that earlier exposure to professional work significantly increases the probability that graduates remain in STEM occupations a decade after graduation. These effects do not operate through improved academic performance or being hired for permanent positions where they interned. Instead, earlier exposure leads students to update their specialization choices during training: the rate of changing major fields roughly doubles among students receiving early second-year exposure, relative to those at the identical stage in the academic program who have not yet received exposure. Students exposed later—after accumulating greater field-specific coursework investments prior to gaining professional experience—are substantially less likely to change fields, consistent with higher switching costs. Field changes predominantly involve switching within engineering rather than exiting altogether, and switchers systematically move toward fields with higher wages and greater alignment with their prior coursework investments. This pattern of updating results in improved long-run matching between graduates and STEM occupations.

These patterns are consistent with a learning-and-matching mechanism playing a role. The timing of professional experience matters because it determines when individuals learn about career fit relative to the accumulation of field-specific investments. Earlier exposure allows individuals to act on this information when switching costs are still low, leading to more efficient sorting across fields and greater long-run attachment to STEM careers. We find no evidence that either the human capital development mechanism or access to opportunities mechanism acts on this margin of incremental shifts in timing of exposure to work experience in the field. It remains possible these mechanisms might operate on different margins in the blends and mix of academics and practice or perhaps with greater magnitues of variation in timing than we observe here.

More broadly, our results contribute to research on human capital development and career

choice under uncertainty by providing causal evidence that the sequencing of education and work experience shapes long-run career trajectories. While prior work has examined whether experiential learning improves short-run academic or labor market outcomes, it has had limited ability to isolate timing effects or to observe long-run retention. By exploiting randomized variation in the timing of professional exposure and following individuals over a decade, we show that the value of experiential learning operates not primarily through enhanced skill formation or access to opportunities, but through earlier resolution of uncertainty about career fit.

The remainder of the paper describes the experimental setting and research design, presents evidence on long-run STEM retention and the underlying mechanisms, and discusses implications for the design of STEM training programs and workforce policy.

2 Research Design

To answer these questions, we study undergraduate engineering students enrolled in a structured training program that combines academic coursework with professional work placements. This setting provides exogenous variation in the timing of professional work experience within a fixed blend of academic training and applied practice. Students complete the same sequence of coursework and work placements but are randomly assigned to when they first receive professional exposure—either earlier or later in their undergraduate trajectory. Because participation in work placements is universal, placements are drawn from a common employer pool, and academic requirements are standardized within field and cohort, both the quantity and institutional quality of work experience are held constant. This design isolates variation in the timing of exposure. We use this variation to estimate effects on long-run STEM retention and to examine intermediate outcomes that distinguish among human capital, opportunity access, and matching mechanisms. In this section, we elaborate on the research design.

2.1 Institutional Setting: A Mandatory Engineering Co-op Program

We study undergraduate engineering students enrolled in a mandatory cooperative education ("co-op") program at a large U.S. research university. The program requires students to alternate between academic coursework and full-time professional work placements over a five-year degree. All students complete a common first-year curriculum before declaring one of several engineering specializations—Biological, Chemical, Civil, Computer, Electrical, and Mechanical Engineering.

Degree requirements include multiple six-month, full-time paid work placements in engineering roles. Students typically complete three co-ops (mean = 2.73), drawn from a centralized employer pool and coordinated through a university placement office. Student quality is high, with average SAT scores of 719 and high school GPAs of 3.99, and the five-year graduation rate is 94 percent. Students earn an average of $19 per hour during co-ops, and 97 percent of placements are in engineering positions. Approximately two-thirds of first co-op placements align with students' declared engineering fields. Placements span a broad set of engineering employers, including large technology firms (e.g., Google), advanced manufacturing companies (e.g., General Electric), and specialized engineering organizations (e.g., Draper Labs).

Co-op positions are curated and monitored by a centralized university office that maintains employer relationships, ensures positions reflect entry-level engineering responsibilities, and manages the matching process. Students apply electronically to posted positions, interview on campus, and receive sequential time-limited job offers, working with assigned placement officers throughout the process.

Because co-op participation is mandatory, placements are drawn from a common employer pool, and academic requirements are standardized within fields and cohorts, this setting isolates variation in the *timing* of first professional exposure rather than whether students receive work experience. All students complete identical coursework for their declared major and face the same progression rules.

2.2 Random Assignment to Early versus Late Exposure

Our study population comprises 1,503 engineering students entering in fall intake cohorts from 2010 through 2014. We exclude transfer students, who are subject to additional requirements for participation in work terms, as well as spring admits, who are not randomized in the same manner. Biomedical engineering students are also excluded, as they do not appear to have been randomized.

Students were randomly assigned to one of two co-op schedules that determine when they begin their first six-month professional placement: Early (spring of second year) or Late (fall of third year). Randomization was conducted administratively within each engineering field and cohort at the end of the first academic year, after students declared their specializations but before any co-op job search or matching.

The randomization procedure was simple and mechanically implemented: within each field-cohort cell, administrators sorted student names alphabetically and assigned alternating students to Early versus Late groups.[1] Both groups complete identical coursework during the first three academic semesters. The schedules diverge in spring of the second year, when Early students take their first co-op while Late students complete their fourth academic semester. Early students return to campus in fall of the third year, when Late students take their first co-op. Thereafter, both groups alternate between academic and work terms, completing the same total number of co-ops by graduation.

Table 1 confirms that randomization successfully balanced observable characteristics. Early (n=749) and Late (n=754) groups are statistically indistinguishable in age, gender composition, financial need, high school GPA, standardized test scores, and pre-randomization college GPA. Characteristics of first co-op placements are also balanced: hourly wages differ by only a few cents, and identical shares of placements match students' declared engineering fields.

Table 1 about here

Importantly, the random assignment of students to co-op schedules was implemented as part of the institution's standard administrative process and was not designed for research purposes.

1. 565 students were assigned an Early (Late) slot upon matriculation but, for reasons unobservable to us, switched to the Late (Early) group. Because we cannot observe the reason for the switch, these students are omitted from our analysis.

We study this variation ex post using anonymized data, without any researcher involvement in assignment or implementation.

2.3 Data and Outcome Measurement

We combine three data sources. First, university administrative records provide student demographics, academic transcripts, declared specializations, and detailed co-op placement information (employer, wages, dates) for all students from enrollment through graduation. These data allow us to track academic performance, measure field switching during training, and classify whether co-op placements align with declared majors.

Second, to measure long-run career outcomes, we collect publicly available LinkedIn profiles through July 2023, matched to university records. We identify alumni based on education fields and enrollment timing, successfully matching 81.2% of engineering students, with similar match rates across treatment groups. A research assistant hand-checks a random sample of matches to verify precision.

We classify employment as Engineering or non-Engineering based on job titles, employer information, and the full text of LinkedIn profiles, using a model-assisted procedure validated by manual review. Roles in marketing, sales, finance, and administration are excluded.

Third, pre-college application data provide high school academic records and standardized test scores, enabling covariate adjustment and heterogeneity analysis.

Our primary long-run outcome is an indicator for whether a graduate is employed in a STEM occupation ten years after degree completion. We also examine narrower definitions restricted to engineering occupations. Our primary short-run outcome is an indicator for whether a student changes engineering specialization during the degree program. We separately analyze switching within engineering versus exits from engineering.

To classify whether co-op placements match students' declared fields, we use employer industry codes, job titles (when available), and the historical distribution of students from each field at multi-field employers. When at least one-third of students from a given field have worked at a firm, we classify that field as a match for the employer.

Main variables used in the analysis are summarized in Table A2.

Table A2 about here

3 Results

This section presents the empirical results. We begin by estimating the effect of earlier versus later first professional exposure on long-run STEM retention. We then examine the mechanisms underlying this effect by testing the three candidate channels motivated in the introduction—human capital development, opportunity and professional network access, and matching of workers to fields.

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3.1 Early Work Exposure Increases Long-Run STEM Retention

We begin by analyzing whether earlier exposure to professional work leads students to stay in Engineering. As described above, we do this by matching student profiles to LinkedIn and classifying their post-graduation jobs as Engineering vs. not. Figure 1 plots the raw year-by-year data. [2]

Figure 1 about here

The y-axis plots the percentage of students who are working in in Engineering-related jobs.[3] Students in the early group begin with a higher percentage working at Engineering jobs, and this gap persists for the full five years. (Note: as our LinkedIn data concludes in 2024, only five years of data are available for students enrolling in 2015.)

In the five-year period following the first post-graduation job, the percentage of years in Engineering by the Early group is 85.7% and by the Late group is 83.7%, a difference of 2%. This entails an additional 1.2 months of work in Engineering on average for an individual student in the

2. We plot years-after-first-post-graduation-job instead of years-after-graduation as some students take a gap year or otherwise do not start their job in the year of graduation.

3. If a student took an engineering job at a firm and then moved into a managerial role at the same firm, we count this as still working in engineering.

Early group for the five years following graduation. In our analyzed cohort of 1,503, this implies 75 additional years spent working in Engineering for the early group.

Of course, the results in Figure 1 do not control for mitigating factors including student demographics including year of admission, the student's Engineering field (i.e., Mechanical), and other factors. In Table 2, we undertake multivariate analysis.

Columns (1-2) replicate the analysis of Figure 1, using as the dependent variable the share of post-graduation years spent in engineering. Without controls there is not a clear difference, but when accounting for student demographics we see a 4.3-percentage-point rise for the Early group (statistically significant at the 5% level). Turning to the number of jobs in columns (3-4), on average, 79% of post-graduation jobs are in Engineering, which rises by 3.8 percentage points for the group with Early exposure to a work term, conditional on fixed effects for cohort and pre-randomization field of Engineering. The estimated coefficient is somewhat larger when accounting for student demographics, although missing data (primarily ethnicity) drop about 100 observations. Columns (5-6) explore another margin: the percentage of students where *all their jobs* five years after graduation are in Engineering. The baseline percentage is 70%, which rises 6-7 percentage points for the Early group. Taken together, the baseline estimates in Table 2 show that earlier exposure to professional work during training promotes retention in engineering.

Figure 1 and Table 2 about here

3.2 Interpretation and Mechanisms: Why Timing of Early Work Exposure Matters

We earlier motivated three distinct mechanisms or channels through which the blend and timing of professional exposure within academic training might affect long-run STEM retention: (i) human capital development, (ii) access to professional opportunities, and (iii) learning and matching. These mechanisms generate different empirical predictions about academic performance, early-career opportunities, and field-switching behavior during training. Each mechanism implies distinct empirical predictions over observable intermediate outcomes—academic performance, early-career opportunities, and specialization switching—which we evaluate in turn."

3.2.1 Early Work Exposure Human Capital Accumulation during Training

What we referred to earlier as the human capital development mechanism reflect a central focus on practice, research, and institutions in engineering education–and implies that the combination and blend of academic training with exposure to practical work reinforces academic learning. To test for whether the *timing* of exposure creates effects on student development on this margin, we test whether the timing treatment leads to differences in academic performance during the degree program. Any change in academic performance could then relate to differences in success and persistence in later careers.

Table 3 examines the impact of early exposure on academic performance. The dependent variable is the student's final recorded GPA in our registrar data. Average GPA among Engineering students is 3.4. Whether including student controls or not, we fail to find any evidence for early work exposure on GPA. These results indicate that early professional exposure does not improve academic performance or accelerate progress through the curriculum. The baseline employment effects documented above are therefore unlikely to be driven by enhanced skill accumulation or academic achievement during training.

Table 3 about here

3.2.2 Early Work Exposure, Professional Networks, and Job Opportunity Access

The opportunity-access and professional networks mechanism described in Section 1 implies that earlier exposure might improve long-run retention if earlier access provides differential access to professional opportunities, such as employer relationships or earlier career development–which could then lead to greater success and persistence within a technical career. If this channel is central, students exposed earlier should obtain systematically stronger early labor-market opportunities, including a greater likelihood of returning to prior internship employers or converting internship placements into permanent post-graduation jobs. We test these predictions using measures of repeat internship relationships and post-graduation employment outcomes.

The first two columns of Table 4 indicate the existence of "return" work terms, where co-op employers re-hire students for successive internships during college. About 14% of students are

re-hired for a return work term at the same company, but this is 4.2 percentage points higher among the Early group. That said, this result is less precisely identified once demographic controls are applied. If this pattern were to carry over post-graduation, we might presume an effect of the Early group having an advantage in securing post-employment Engineering jobs, at least at the same company. Although one-fifth (21%) of students are hired permanently by one of their work-term employers. However, in columns (3-4) we fail to find evidence that this differs between the Early or Late groups. It may still be that earlier internships facilitate connections via professional networks to employment opportunities at Engineering companies where the student did not do a co-op. Outside of that possibility, these findings do not provide evidence that differential access to early job pipelines accounts for the observed effects on this margin.

Table 4 about here

3.2.3 Early Exposure and Worker-Field Specialization Matching

The worker–field matching mechanism described in Section 1 implies that earlier professional exposure can help individuals acquire information about the fit between their aptitudes and interests and their chosen field of specialization. When this information arrives earlier—before substantial field-specific investments are made—it should increase the likelihood that individuals act on it, either by affirming their current specialization or by switching to a better-matched field. By contrast, individuals who receive exposure later may be less responsive to such information, as prior investments in a given field raise the costs of adjustment and increase the likelihood of remaining in a potentially suboptimal match. We test these predictions by examining switching behavior across and within fields, as well as the timing of these adjustments relative to initial exposure.

The dependent variable in columns (1-2) of Table 5 is an indicator for whether a student changes majors, including to non-Engineering majors or to different fields within Engineering (which count as different majors at the University). Approximately 3.3 percent of the Engineering students switch their major, a figure that rises by 3.2 percentage points in the Early group—effectively doubling the likelihood of switching majors.

The remaining columns of Table 5 decompose switching between changing majors *within* Engi-

neering vs. leaving Engineering entirely. Most students who switch do so within Engineering (2.6% of the 3.3% who switch). Columns (3-4) show that early exposure raises the probability of switching to another major within Engineering by an additional 2.0 percentage points. This represents a near-double increase in specialization adjustment at this margin.

The remaining two columns of Table 5 explore switching out of Engineering entirely. About half a percent of students leave Engineering after their first work term. Columns (5-6) indicate that the Early group is more than twice as likely to switch out. Interestingly, the overall persistence of the Early group in Engineering jobs observed in Figure 1 and Table 2 occurs despite them being more likely to graduate in a non-Engineering major. This suggests that refining one's specialization within Engineering promotes long-term retention for those who graduate in Engineering, despite more students leaving Engineering entirely. (Note: Figure 1 does *not* omit students who switched out of Engineering and graduated in another major.)

Table 5 about here

Two features of the results reinforce a learning-based interpretation. First, the timing of the response is tightly linked to information arrival: switching increases precisely in the semester immediately following the first professional work experience. Second, the comparison holds constant academic stage and cohort and includes fixed effects for the student's pre-randomization engineering field, ruling out explanations based on differential curriculum progression or cohort-specific labor market conditions.

Moreover, we find that this change is driven by exposure to internships within one's planned Engineering field. We develop a measure of whether the work-term internship matches one's major prior to randomization using the procedure outlined in Appendix A, Table 6 examines switching contingent on the internship matching the student's existing field. About 37% of internships match the student's pre-randomization field of Engineering and are examined in column (1). Column (2) analyzes the subsample of students whose first work term did not match. The base rate of switching is lower among those whose first work term matched (1.3%, vs. 3.7% for those whose work term did not match their Engineering major). Among those with a "matched" work term the switching rate is nearly triple for the Early group.

One interpretation of this is that the initial major selection, made under uncertainty, is refined by the work term where the student is exposed to real-world experience. Another interpretation is that the early group with "matched" work terms switches because their first work term was premature, and their sense of failure led them to switch to another field. Our data cannot conclusively distinguish between these possibilities.

In the remainder of Table 6 we explore the role of choice vs. serendipity in this learning process. Students are randomly assigned to Placement Coordinators, who work with them to find an internship where they can spend their work term. The likelihood that each Placement Coordinator assigns a focal student to a work term that matches their major is determined from the probability that that Placement Coordinator assigned every other of their advisees to a major-matching work term. (This likelihood is calculated only for Placement Coordinators with at least ten advisees; students assigned to Placement Coordinators with fewer than ten advisees are omitted from IV estimates.) The instrument is then calculated as a residual prediction. The first stage of this instrument, in column (3), is a strong predictor of whether a student obtains a major-matched internship. However, the second stage of this instrument, where the instrumented coop-major-match is interacted with the Early vs. Late internship, does not appear predictive, i.e., the estimated coefficient on *Work term matched major X early* is not precisely estimated.

Table 6 about here

3.2.4 Results Summary

Taken together, the evidence is consistent with earlier exposure shaping long-run STEM retention through a worker–field matching channel on the margin we study. Earlier exposure increases field-switching behavior precisely at the point when new information arrives, particularly within engineering fields, and this adjustment occurs precisely when switching costs remain relatively low. These patterns are consistent with earlier exposure enabling individuals to update their specialization choices in response to information about fit, leading to improved alignment between individuals and fields and, in turn, greater long-run retention in STEM occupations.

We find no evidence that earlier exposure improves academic performance, nor do we find

evidence that it enhances early-career opportunity pipelines. This does not imply that human capital development or opportunity access are unimportant in the broader academic–practicum mix; rather, within the margin we identify—variation in the timing of exposure holding the overall blend of academic training and work experience constant—we do not find evidence that these channels account for the observed effects.

4 Discussion and Conclusion

This paper set out to examine whether the timing of professional work exposure during applied STEM training affects long-run retention in STEM occupations. The results point to a clear interpretation. Early professional exposure does not improve academic performance or improve the chances of being re-hired by one's work term employer. Instead, it increases long-run STEM retention by enabling students to make better specialization choices when switching costs are still low. These findings help clarify the relationship between two influential but distinct perspectives on applied STEM training. A longstanding view in engineering education and learning science emphasizes the value of integrating professional practice with academic instruction to enhance learning, skill acquisition, and applied competence. From this perspective, the central concern is whether experiential learning improves the quality of human capital accumulation. Our results suggest that, at least in this setting, the timing of substantial professional exposure does not meaningfully affect these learning-related outcomes. Academic performance and the quality of initial work placements are largely invariant to whether exposure occurs earlier or later in the training sequence. By contrast, the evidence is strongly consistent with a second perspective, common in economics, that emphasizes learning about preferences, aptitudes, and match quality over the course of human capital investment. From this viewpoint, professional experience serves not primarily to raise productivity, but to reveal information about fit across fields and career paths. Early exposure allows this information to arrive before substantial field-specific investments accumulate, facilitating corrective re-sorting within engineering specializations. Later exposure, by contrast, arrives after switching costs have risen, reducing the scope for adjustment even when mismatches are revealed. The timing of experience therefore matters less for how much students learn than for what they

choose to do with what they learn. This distinction helps reconcile why extensive integration of projects, labs, and practicum throughout engineering curricula may succeed in supporting learning outcomes, while still leaving open an important role for the timing of immersive professional work in shaping long-run career trajectories. Human capital accumulation appears relatively robust to when practice is introduced, but career matching and retention are not. Early exposure affects who remains in applied STEM work not by producing better engineers, but by helping individuals find better-fitting engineering roles. These findings have implications for the design of applied STEM training programs. Policies aimed at improving STEM retention often focus on expanding access, increasing enrollment, or enhancing instructional quality. Our results suggest that comparatively modest changes in the sequencing of professional exposure—without altering total training content or quality—can have lasting effects on workforce composition. More broadly, the results highlight the importance of distinguishing between interventions that improve productivity and those that improve sorting when evaluating the long-run impacts of educational and training policies.

Table 1: Balance on Observables Among Students Randomly Assigned to Early vs. Late Groups - where LinkedIn data is available

	# early	# late	Mean early	Mean late	p-value
Age	513	586	18.347	18.307	0.392
Female	513	586	0.211	0.224	0.602
Underrepresented Minority	466	540	0.118	0.111	0.731
International student	513	586	0.084	0.056	0.073
Low-income student	513	586	0.057	0.084	0.081
High-school GPA	487	579	3.988	4.039	0.014
Percentile on standardized tests	465	546	0.857	0.871	0.000
GPA as of 3rd semester	513	586	3.352	3.385	0.211
Credits as of 3rd semester	513	586	52.955	53.208	0.160
First work term in U.S.	512	585	0.969	0.969	0.963
First work term wage	502	570	18.990	19.116	0.733
First work term in Engineering	498	577	0.946	0.953	0.579
Work term matched major	389	480	0.378	0.373	0.880

Notes: No. obs = 1,503 students. The second and third column shown counts for each variable for students randomly assigned to Early vs. Late groups, followed by means. The sixth column shows the p-value from a difference-of-means test.

Table 2: Early exposure and staying in engineering after graduation (5 years)

Dep. Var.:	Percentage of years spent in Engineering		Percentage of all jobs in Engineering		All jobs are in Engineering	
	(1)	(2)	(3)	(4)	(5)	(6)
Early work exposure	0.0336	0.0434**	0.0378*	0.0459**	0.0636**	0.0737**
	(0.0209)	(0.0220)	(0.0210)	(0.0220)	(0.0277)	(0.0289)
Female		-0.0558*		-0.0606**		-0.0705*
		(0.0294)		(0.0296)		(0.0378)
Low-income student		-0.0360		-0.0347		-0.00649
		(0.0470)		(0.0474)		(0.0569)
Underrepresented Minority		-0.0126		-0.0135		-0.0435
		(0.0366)		(0.0367)		(0.0487)
Observations	1099	1006	1099	1006	1099	1006
Mean of DV	0.804	0.802	0.793	0.792	0.701	0.701
Cohort FE	yes	yes	yes	yes	yes	yes
Pre-randomization Eng. field FE	yes	yes	yes	yes	yes	yes

This table compares switching for Early vs. Late internship groups in the Fall semester of Year 3. As shown in Table A1, this is the semester right after the Early group returns from their first internship and when the Late group has not yet returned from their first internship. No. obs = students, for whom we were able to find informative LinkedIn profiles. Jobs from LinkedIn are classified into Engineering fields as described in Appendix **??**. All models have fixed effects for the student's year of admission and pre-randomization Engineering field. Robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Early exposure and GPA

Dep. Var.:	GPA	
	(1)	(2)
Early work exposure	-0.00366	-0.00882
	(0.0254)	(0.0260)
Female		0.0907***
		(0.0302)
Low-income student		0.234***
		(0.0453)
Underrepresented Minority		-0.219***
		(0.0456)
Observations	1090	998
Mean of DV	3.400	3.398
Cohort fixed effects	yes	yes
Pre-randomization Eng. field	yes	yes

Notes: This table compares switching for Early vs. Late internship groups in their fourth semester of classes. As shown in Table A1, this is the semester right after the Early group returns from their first internship (Fall of Year 3) and before the Late group undertakes its first internship (Spring of Year 2). No. obs = 1,503 students. All models have fixed effects for the student's year of admission and pre-randomization Engineering field. Robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Early exposure and labor market advantage

Dep. Var.:	Repeat internships		Job at graduation from internship	
	(1)	(2)	(3)	(4)
Early work exposure	0.0417**	0.0352	-0.0143	-0.0176
	(0.0211)	(0.0217)	(0.0247)	(0.0260)
Female		-0.0314		-0.0181
		(0.0232)		(0.0320)
Low-income student		-0.0212		0.0279
		(0.0353)		(0.0609)
Underrepresented Minority		0.00212		-0.00157
		(0.0342)		(0.0417)
Observations	1044	954	1009	925
Mean of DV	0.143	0.134	0.210	0.214
Cohort fixed effects	yes	yes	yes	yes
Pre-randomization Eng. field	yes	yes	yes	yes

Notes: This table compares switching for Early vs. Late internship groups in their fourth semester of classes. As shown in Table A1, this is the semester right after the Early group returns from their first internship (Fall of Year 3) and before the Late group undertakes its first internship (Spring of Year 2). No. obs = 1,503 students. All models have fixed effects for the student's year of admission and pre-randomization Engineering field. Robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Early exposure and switching majors

Dep. Var.:	Switched major		Switched within Engineering		Switched out of Engineering	
	(1)	(2)	(3)	(4)	(5)	(6)
Early work exposure	0.0320***	0.0312***	0.0201**	0.0193*	0.0119***	0.0119**
	(0.0104)	(0.0111)	(0.00947)	(0.0101)	(0.00451)	(0.00484)
Female		0.0139		0.00969		0.00423
		(0.0146)		(0.0133)		(0.00624)
Low-income student		-0.0151		-0.00244		-0.0126**
		(0.0218)		(0.0210)		(0.00622)
Underrepresented Minority		0.00174		-0.0250**		0.0267
		(0.0206)		(0.0121)		(0.0170)
Observations	1090	998	1090	998	1090	998
Mean of DV	0.0330	0.0341	0.0266	0.0281	0.00642	0.00601
Cohort fixed effects	yes	yes	yes	yes	yes	yes
Pre-randomization Eng. field	yes	yes	yes	yes	yes	yes

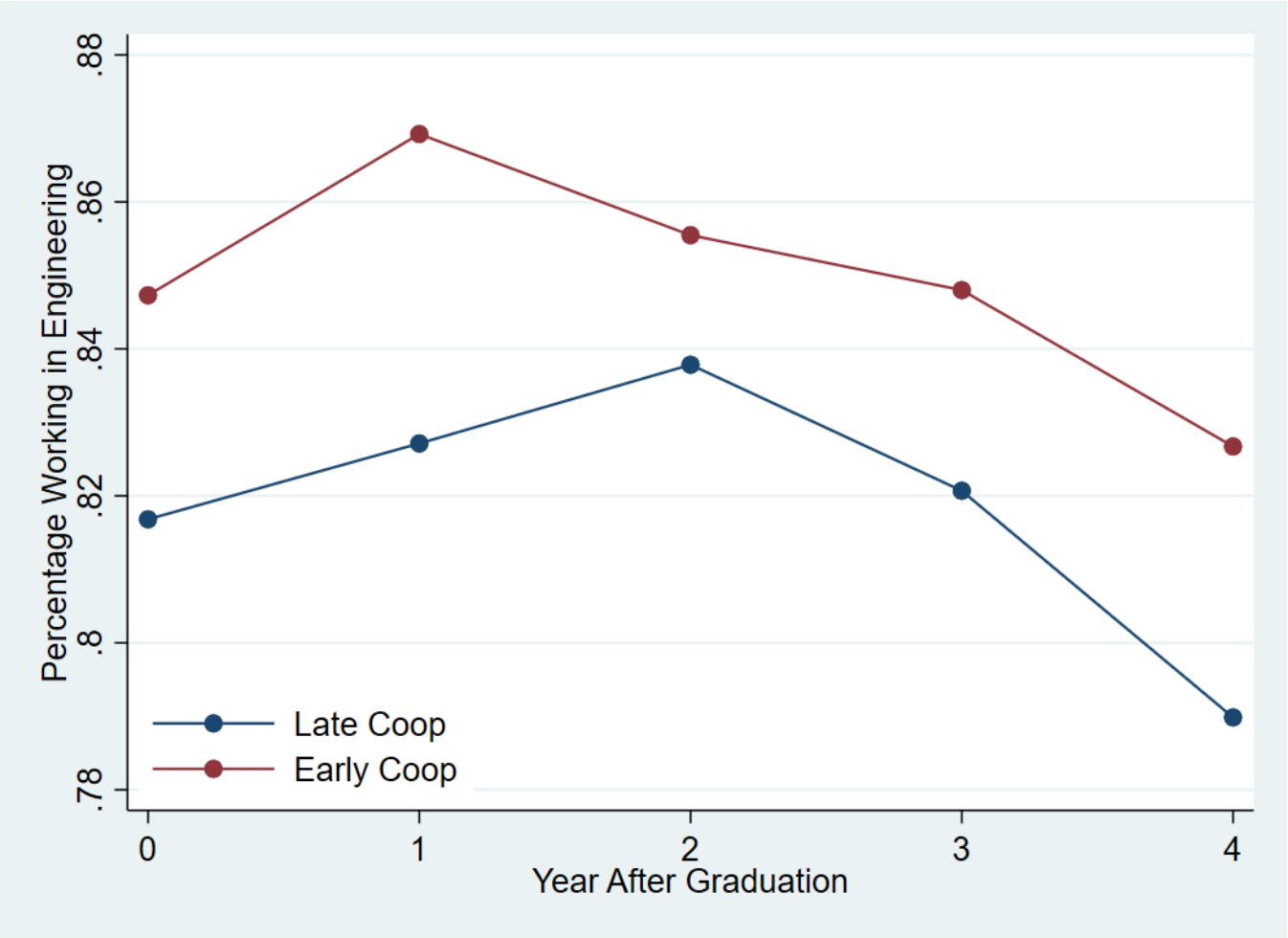
Notes: This table compares switching for Early vs. Late internship groups in their fourth semester of classes. As shown in Table A1, this is the semester right after the Early group returns from their first internship (Fall of Year 3) and before the Late group undertakes its first internship (Spring of Year 2). No. obs = 1,503 students. All models have fixed effects for the student's year of admission and pre-randomization Engineering field. Robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Early exposure and switching specializations, by matched work term

Dep. Var.: Switched major within Engineering				
Internship matches major	yes	no		
	(1)	(2)	(3)	(4)
Early work exposure	0.0255**	0.0263		0.0355
	(0.0129)	(0.0168)		(0.0221)
Female	0.0186	0.00806		0.00815
	(0.0190)	(0.0222)		(0.0155)
Low-income student	-0.0128	0.00160		-0.00103
	(0.0117)	(0.0290)		(0.0197)
Underrepresented Minority	-0.0116	-0.0470***		-0.0346***
	(0.00732)	(0.0138)		(0.00908)
Share Advisees w/matched major			0.961***	
			(0.143)	
Work term matched major				-0.00303
				(0.0466)
Work term matched major X early				-0.0315
				(0.0452)
Observations	298	488	855	754
Mean of DV	0.0134	0.0369	0.379	0.0279
First-stage F				39.67
Cohort fixed effects	yes	yes	yes	yes
Pre-randomization Eng. field	yes	yes	yes	yes

Notes: This table compares switching for Early vs. Late internship groups in their fourth semester of classes. As shown in Table A1, this is the semester right after the Early group returns from their first internship (Fall of Year 3) and before the Late group undertakes its first internship (Spring of Year 2). No. obs = 1,503 students. All models have fixed effects for the student's year of admission and pre-randomization Engineering field. Robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1: Year-by-year Post-Graduation STEM Retention



Notes: 1,503 students total. X-axis is the number of years since graduating. Y-axis is percentage of students that year (with data in LinkedIn) who are in an Engineering job.

Appendices

A Classifying internships into Engineering fields

We determine whether the internship is in the same field as the student's original Engineering specialty. The registrar data contains the name of the internship employer and the firm's industry. If the industry is specific we map it directly to an Engineering specialty. For example, Construction can reliably be mapped to Civil Engineering. However, several industries are classified quite broadly, such as "Services" or "Manufacturing." (For example, Amazon.com is listed as "Services.") Others have a blank industry code. In these cases we look up companies' internet profiles and, if possible, classify them into a narrow industry that maps to an Engineering specialty.

Many firms cannot be categorized into a single Engineering major, so we allow multiple majors per firm based on the distribution of students who intern there. For example, Apple takes many Computer Engineering students but also a number of Electrical and Mechanical Engineers. E-Ink brings in a similar number of Chemical and Mechanical engineers. If at least one-third of the students who spent their work term at that firm was initially in a particular Engineering specialty, we include that specialty for the firm. Students whose initial specialty maps to any of the Engineering specialties associated with their internship employer are said to have a match.

When job titles are available, we further use these to resolve the field. Job titles such as "Intern" are uninformative, but where we can extract words such as Chemical or Software the student's work term can be directly mapped to an Engineering major. Two-thirds of of students () matched their internship to their original Engineering specialty.

Table A1: Sequence of Coursework and Internships for Students Randomly Assigned to Early vs. Late Groups

	Year 1		Year 2		Year 3		Year 4		Year 5	
	Fall	Spring	Fall	Spring	Fall	Spring	Fall	Spring	Fall	Spring
Early	Classes	Classes	Classes	*Internship*	Classes	*Internship*	Classes	*Internship*	Classes	Classes
Late	Classes	Classes	Classes	Classes	*Internship*	Classes	*Internship*	Classes	*Internship*	Classes

Note: Table shows the sequence of classes vs. internships for students randomly assigned to Early vs. Late groups. Students must declare an Engineering field at the end of the Fall semester and are randomly assigned by the end of the Spring semester. Both groups are on campus taking classes during the first three academic semesters. Beginning in the Spring of Year 2, the two groups alternate between Classes and *Internship* until the final semester of Year 5, when both groups are again on campus taking classes. From the fourth until penultimate semester, the two groups are not on campus at the same time. The Early group takes classes in the Spring, and the Late group takes classes in the Fall. Accommodating three six-month internships before graduation stretches the program to five years. Students are required to complete at least one internship to graduate, but most complete three (average = 2.7). Internships are longer than academic semesters; Fall internships run July-December and Spring internships run January-June. The Early and Late groups graduate together at the end of Year 5.

Table A2: Variable definitions

Pre-randomization GPA	Student grade point average prior to randomization (i.e., as of the end of the Fall semeste
Student age	Age of student upon enrolling at the university.
Female student	Registrar records report student is female.
FAFSA-based financial need (ln)	Assessed financial need according to FAFSA (may differ from actual award from the univ
High-school GPA	Student's grade point average during high school (not normalized by high-school or cours
Percentile on standardized tests	Average percentile of math and verbal on SAT, ACT, or both
Num. credits taken by 3rd sem.	Number of credits taken by student as of the end of the Fall semester of Year 2
Pre-randomization pct. courses in engineering	Percentage of courses as of the end of the Fall semester of Year 2 taken in the Engineerin
Changed field	Student changed from original Engineering field, either to another Engineering field or a lowing Fall semester of Year 2
Changed to another Engineering field	Student switched from original Engineering field to another Engineering field, following F
Changed to non-Engineering field	Student switched from original Engineering field to non-Engineering field, following Fall s
Hourly wage during first internship	Hourly wage in dollars earned by the student during their first internship
Students at internship firm (ever)	Total number of students who completed an internship at the same firm as the focal stud
Same-field students ever at internship firm	Number of students from the same Engineering field who completed an internship at the sa between 2009 and 2017
Internship students supervised by boss	Number of students at the same internship firm who had the same supervisor as the focal
Female internship boss	Given name of student's supervisor at first internship appears to be female
Students at employer during internship	Number of students at the same internship firm at the same time as the focal student
Same-field students at internship	Number of students from the same Engineering specialization who completed an internsl same time as the focal student
Internship matches pre-randomization field	The internship took place in the same field as the student's pre-randomization Engineerir
Course-work based Euclidean distance	Euclidean distance between the student's pre-randomization Engineering field and anothe the student *might have changed* (whether or not the change actually took place)
Post - pre avg. internship wage	Difference in the average internship wages for those in the student's pre-randomization E average wages in another Engineering field to which the student *might have changed* (actually took place)
Post - pre avg. GPA	Average GPA for all students in the student's pre-randomization Engineering field, minus t Engineering field to which the student *might have change* (whether or not the change act

Note:

Table A3: Early exposure and switching majors as of 4th semester

Dep. Var.:	Switched major		Switched within Engineering		Switched out of Engineering	
	(1)	(2)	(3)	(4)	(5)	(6)
Early work exposure	0.0320***	0.0312***	0.0201**	0.0193*	0.0119***	0.0119**
	(0.0104)	(0.0111)	(0.00947)	(0.0101)	(0.00451)	(0.00484)
Female		0.0139		0.00969		0.00423
		(0.0146)		(0.0133)		(0.00624)
Low-income student		-0.0151		-0.00244		-0.0126**
		(0.0218)		(0.0210)		(0.00622)
Underrepresented Minority		0.00174		-0.0250**		0.0267
		(0.0206)		(0.0121)		(0.0170)
Observations	1090	998	1090	998	1090	998
Mean of DV	0.0330	0.0341	0.0266	0.0281	0.00642	0.00601
Cohort fixed effects	yes	yes	yes	yes	yes	yes
Pre-randomization Eng. field	yes	yes	yes	yes	yes	yes

Notes: This table compares switching for Early vs. Late internship groups in their fourth semester of classes. As shown in Table A1, this is the semester right after the Early group returns from their first internship (Fall of Year 3) and before the Late group undertakes its first internship (Spring of Year 2). No. obs = 1,503 students. All models have fixed effects for the student's year of admission and pre-randomization Engineering field. Robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.