The Impact of Choice Architecture on Postsecondary STEM Enrollment: Evidence from a Randomized Controlled Trial

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1 Background

Despite a dramatic increase in college attendance rates among women, the proportion of technology and engineering degrees awarded to women has declined from a peak of 37.1% in 1984 to the current level of 18% (National Science Foundation, 2015). Lower levels of technology skill investment among women persist even as technology and engineering occupations have become more desirable and in greater demand. This decline in STEM degree attainment among women has broader consequences for the workforce. Although women obtain more than half of all bachelors' degrees, the distribution of majors that men and women choose across all fields has produced a concentration of women in low-paying fields (Goldin et al., 2006). Occupational segregation is the largest driver of gender-based differences in earnings, accounting for 51% of the gender pay gap (Blau and Kahn, 2016).

Sorting across college majors is primarily driven by differences in abilities, preparation, and preferences, with preferences for particular majors being most important (Altonji et al., 2012; Arcidiacono, 2004). Controlling for abilities and preparation, women tend to prefer female-dominated fields such as education and psychology over technology and engineering, in part due to bias resulting from gender stereotypes and poor information about technology and engineering occupations. From an early age, girls and boys are socialized to see computing as masculine (Margolis and Fisher, 2002). Since technology skills are considered elective rather than core academic skills among primary and secondary educational institutions, girls receive little information about how technology education relates to their occupational interest and goals (Margolis, 2008).

To address the effects of stereotypes and poor information, several small, STEM-focused institutions of higher education have implemented interventions aimed at providing students with better information and higher-quality experiences with technology (Corbett and Hill, 2015). Early evidence suggests that these interventions were effective, having doubled the proportion of women among computing and engineering majors to approximately 40%. However, the interventions are time-intensive, costly, and difficult to scale. Employing similar efforts across a wider range of institutions would require major changes to curricula, coordination across many stakeholders, and funding for costly extracurricular activities.

2 Research Question

This study describes a randomized experiment in which college freshmen received structured information about technology courses during orientation. I consider whether this strategic change in choice architecture, or nudge, led to higher STEM participation as measured by enrollment in technology courses.

3 Setting and Population

Study participants included approximately 4,000 first-time, full-time college students at a flagship public university located in the Midwest.

4 Intervention

In past years, each student typically received an unstructured list of available courses during new student orientation. In contrast, students in the treatment group received a four-page brochure intended to nudge students whose preferences are aligned with technology course offerings. The brochure listed technology courses from across academic fields along with a description, the number of credits, and the semesters that the course is typically offered. Courses were included only if they had no prerequisites and as long as they met one or more of the following criteria: provided training in a particular software or hardware; utilized technological assets as part of its core; prominently featured computing, digital assets, or digital skills; surveyed the technologies that are relevant for disciplinary applications; or developed an applied skill that is a stated or implied learning outcome of the course.

5 Research Design

Figure 1 outlines a student's pathway from registering for orientation to enrolling in courses. Each student's family chooses one of 23 orientation sessions and attends on campus for two days. I randomly assigned each orientation session to a treatment or control condition, with each orientation cohort comprising 180 students on average. Students were assigned at the cohort level in order to minimize peer spillover effects. Since students visit campus for two days, several weeks prior to moving onto campus, attendees within each cohort encounter only those students receiving the same intervention. Approximately two-thirds of students were in cohorts assigned to the treatment group.

6 Data and Methodology

I estimate the impacts of the intervention using both a difference of means and a logistic regression framework. Students are clustered within cohorts and within advisors, and course enrollments are clustered within students. To address the lack of independence between observations, I specify a mixed-effects generalized linear model, including a random intercept for each student.

$$Pr(\hat{Y}_c = 1) = \text{logit}^{-1}(\beta_{0[s]} + \beta_k X_s + \beta_j X_c + \epsilon)$$

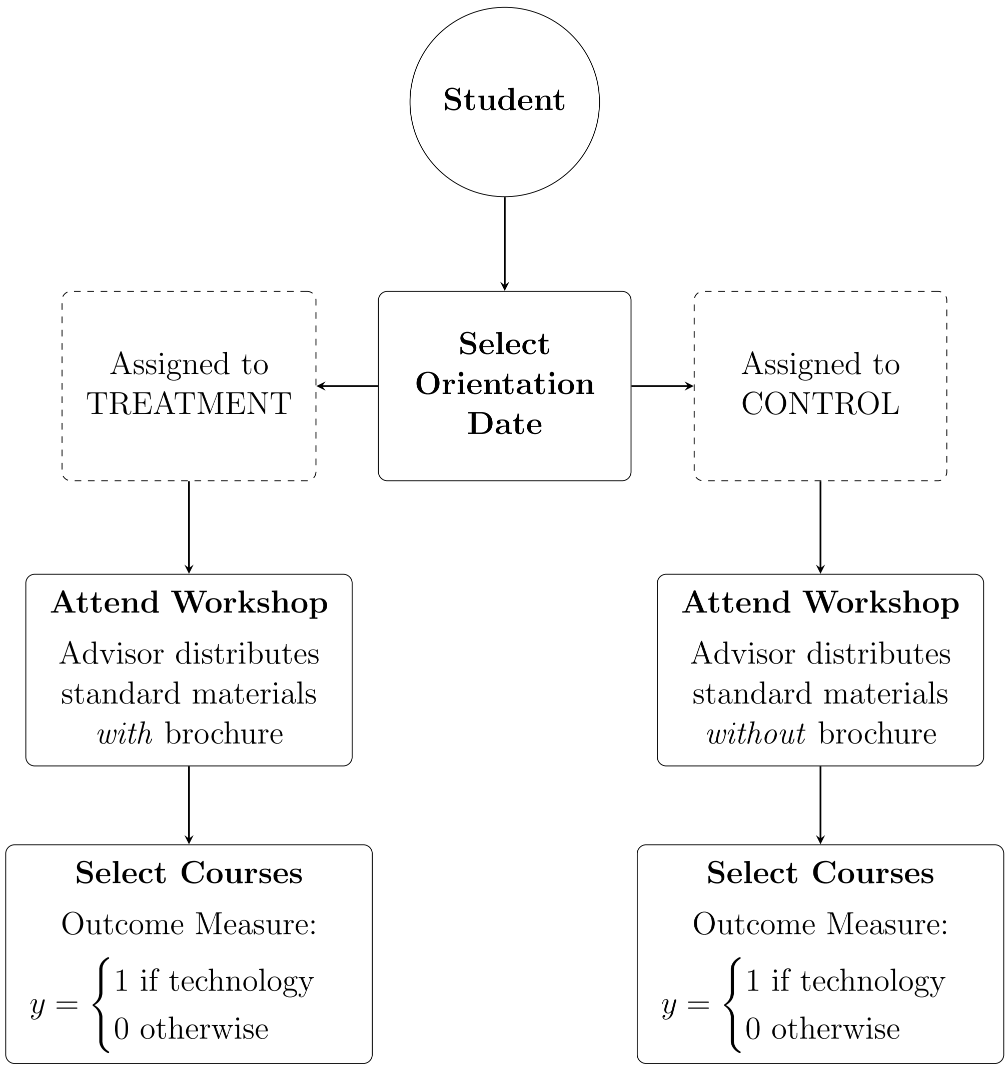
where $\beta_{0[s]}$ is the set of random intercepts for each student, X_s is the set of pre-treatment covariates at the student level, and X_c is the set of covariates at the course enrollment level.

In aggregate, 4,287 students participated in the experiment. Student-level pre-treatment covariates include gender, minority status, age, and ability. I constructed the ability measure using the math SAT and ACT sub-scores, converting all scores to percentiles. For each enrollment, I constructed term day as the difference in days between the student's orientation enrollment date and the first available orientation date. Term day captures the effect of institutional structure on the number of seats available for each course.

7 Findings

The intervention increased the baseline take-up rate by 2.8 percentage points for the fall semester, and by 0.9 percentage points for the spring semester. These values correspond to substantively large effect sizes of 0.64 and 0.20 standard deviations for fall and spring enrollment, respectively. Students in the treated cohorts were more likely to enroll in a technology course for the fall semester. Among male students, the treatment effect persisted from the fall to the spring semester, with average treatment effects of 3.0 and 2.6 percentage points, respectively. Female students in the treatment group were more likely to choose a technology course in the fall semester, but slightly less likely in the spring semester, with treatment effects of 2.7 and –0.6 percentage points, respectively. Since the increased take-up for the fall is more than four times the decrease for the spring, female students may be responding to new information rather than shifting the timing of courses that they would have taken anyways from the spring to the fall. The magnitude of the effect sizes provides strong evidence that a small change to the choice architecture can influence students' decision to invest in technology skills through postsecondary coursetaking.

8 Tables and Figures



Notes: Students selected one of 23 two-day orientation cohort and each cohort was randomly assigned to treatment or control conditions. Within a given cohort, each student attended a workshop facilitated by one of 19 academic advisors. Each student then enrolled in four to six courses. The outcome for each course enrollment takes a value of one if the course was listed in the treatment brochure and zero otherwise.

Figure 1: Experimental Design

Table 1: Descriptive statistics by treatment condition

Covariate	All	Treatment	Control	Difference	Std. Difference
Female	0.516	0.519	0.518	0.0029	0.006
	0.500	0.500	0.500	-0.0002	
Minority	0.118	0.111	0.113	-0.0066	-0.021
	0.322	0.314	0.317	-0.0081	
Age	18.427	18.390	18.402	-0.0375	-0.084
	0.510	0.413	0.446	-0.0968	
Ability	77.333	76.822	76.986	-0.5109	-0.041
	12.199	12.427	12.355	0.2281	

Table 2: Technology course take-up by treatment condition

Term	Gender	Control	Treatment	Difference	Pct. Difference
Fall	All	0.250	0.278	0.028	11.2
Fall	Female	0.176	0.203	0.027	15.2
Fall	Male	0.328	0.358	0.030	9.2
Spring	All	0.317	0.326	0.009	2.9
Spring	Female	0.217	0.211	-0.006	-2.7
Spring	Male	0.421	0.447	0.026	6.3

Table 3: Estimated enrollment in technology courses

	$\hat{\beta}$	SE
Treatment	0.112^{**}	(0.050)
Treatment x Ability	-0.282^{***}	(0.104)
Ability	0.367^{***}	(0.097)
Female	-1.011^{***}	(0.049)
Female x Ability	0.291^{***}	(0.105)
Minority	-0.196^{**}	(0.082)
Minority x Female x Ability	-0.613^{***}	(0.183)
Age	-0.027	(0.046)
Spring Term	0.215^{***}	(0.031)
Term Day	-0.217^{***}	(0.058)
Term Day x Spring Term	0.175^{***}	(0.063)
Constant	-2.549^{***}	(0.052)
N	61,218	
Note:	***p < .01; **p < .05; *p < .1	

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